Development of low cost EMG data acquisition system for Arm Activities Recognition

A Dissertation submitted in fulfillment of the requirements for the Degree

of

MASTER OF ENGINEERING

in

Electronic Instrumentation Control Engineering

Submitted by

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DECLARATION

I hereby certify that the work which is being presented in this thesis entitled, "**Development of low cost EMG data acquisition system for Arm Activities Recognition**" in fulfillment of the award of degree of **Master of Engineering degree** in **Electronics Instrumentation and Control Engineering** submitted in ELECTRICAL & INSTRUMENTATION Engineering Department of **Thapar University, Patiala**, is an authentic record of work carried out by me under the supervision and guidance of **Dr. Ravinder Agarwal, Professor** of **Electrical and Instrumentation Engineering Department, Thapar University, Patiala**.

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I certify that the above statement made by the student is correct to the best of my knowledge and belief.

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Lastly, I would like to thank my parents for their unconditional support and encouragement. They have always wanted the best for me and admire their determination and sacrifies.

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LIST OF ABBREVIATIONS

EMG	Electromyogram
ECG	Electrocardiogram
EEG	Electroencephalogram
MUAP	Motor unit action potential
PGA	Programmable gain Amplifier
SPS	Samples per second
CMRR	Comman mode rejection ratio
PCB	Printed circuit board
SVM	Support vector machine
LDA	Linear discriminent analysis
A/D	Analog to Digital
GUI	Graphical user interface
IC	Integrated circuit
DAQ	Data Acquisition
KNN	K-Nearest Neighbour
ANOVA	Analysis of variance
ANN	Artificial neural network

ABSTRACT

Electromyography (EMG) signals are becoming continuously more important in many fields, including biomedical/clinical, prosthesis, human machine interaction and rehabilitation devices. Due to its undesirability to drive display and monitoring systems, it needs an adaptable and robust enough processing units to clearly picture the signal. In the present study, to meet the requisites of EMG data acquisition systems, a high resolution, and highly competitive eight channel system has been developed, which is cost efficient and compact as compared to commercially available systems. To validate the developed system, EMG signals have been acquired from various muscles for different arm activities and also machine learning techniques were utilized for activity recognition. For the current study 8 Male and 4 Female healthy subjects were recruited. For classification purpose various time and frequency domain features were extracted and two kind of feature selection techniques were utilized. The classification accuracy ranges from 43.64% to 92.61% for different classification algorithms. Further comparative study of different classification techniques is presented. After the selection of features accuracy 92.66% has been achieved with only two muscles’s contribution and this work has been compared with previous research. For this piece of work MATLAB 15a is utilized for signal processing and machine learning.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Muscles are the part of the human body. In order to understand the mechanism of human physique, the study of electromyography (EMG) is essential. Any body part can be moved with the help of the coordination brain, muscles and nervous system. The brain control the limbs joints with the help of 28 muscles to produce forces which are required against the gravity and tends to move the body forward with less amount of energy used [1]. Brain coordinates with the muscles to move the parts of body. The excitation signal is sent from brain through Central Nervous System (CNS) to the appropriate muscle which is to be moved. Combination of muscles in groups is called ‘Motor Units’. The summing point where the motor neuron and the muscle fibres meets each other is called motor unit. A depiction of the Motor Unit is given in Figure 1.1. ‘Motor Unit Action Potential’ (MUAP) is produced whenever motor unit is activated [2]. Central Nervous System activates the nerve as long as appropriate amount of force is not generated in the required muscle. This continuity is required to train the motor unit action potential. These trainings from concurrently active motor units superimpose to produce the resultant EMG.

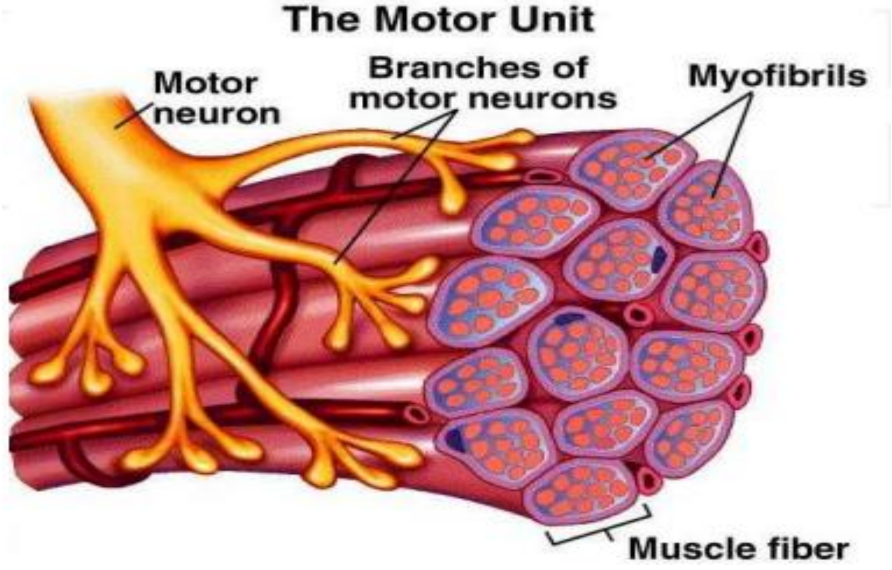

Figure 1.1 The motor unit

1.2 Importance of surface EMG:

1. Biomechanics and movement analysis: This includes the identification of muscle activation intervals and levels, muscle coordination.
2. Muscle fatigue and non invasive fiber typing: It includes the monitoring of myoelectric manifestations of electrical responses, muscle fatigue, and mechanical responses of single motor units[3].
3. Muscle physiopathology: Monitoring muscle fibre conduction velocity, motor unit recruitment order.
4. Rehabilitation, space and sports medicine: Assessment of effectiveness of treatments and training, monitoring microgravity related changes and effectiveness of counter measures [4-5].
5. Pelvic floor analysis: Detection of sphincter asymmetry, prevention of episiotomy related lesions.
6. Biofeedback: Tension headache, muscle retraining, coordination retraining.

1.3 Motivation

Many research have been carried out in Electromyography for decades, with recent advancements in electronics science and computation science, rehabilitation, kinesiology, occupational and sports medicine are the main focuses of surface EMG.

Many people lost their limbs due to accident, trauma or any disease affecting the limb and this number is increasing day by day [6]. These people cannot even perform their daily routine work such as holding object, eating, moving an object and all these kind of work. One solution for these kinds of people is EMG based prosthetic device. EMG based prosthetic device, as name suggest the EMG signal use to control the action with the help of motor.

Although many signal software processing techniques and high level applications of EMG signals are available and being developed nowadays, but they are expensive (e.g. BIONOMADX, NeXus-10) and also system developed based on ICs INA128 or INA2141 (Instrumentation amplifiers) are complex in design and provide time delay in signal processing [7-10]. Hence there is a need of a system having multichannel, lower price and compact in design.

1.4 Basic architecture of EMG signal acquisition

EMG signal has limited bandwidth of electric potentials lie within 20 to 500 Hz and its amplitude ranges from 50uV to 20-30mV peak-to-peak, it depends upon the intensity of muscle contraction [9]. Signal detection is acquired at first, further amplification part is done, then comes the conditioning and digitization of surface EMGs. This process is clearly shown in the block diagram in Figure 1.2.

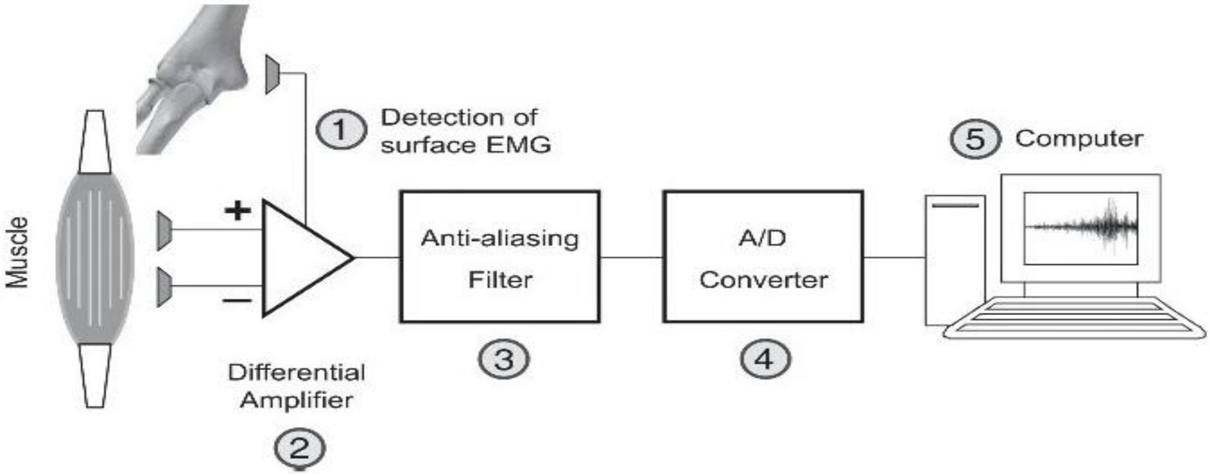

Figure 1.2 Block diagram of acquisition of EMG signal [10].

Amplification (block 2 in Figure 1.2) of the detected EMG signals is important to match the amplitude with the dynamic range of the A/D converter (block 4). In electromyographic systems, the dynamic range of A/D converter varies from ± 2.5 V to ± 10 V. Due to this reason, amplification is needed for the small surface EMGs signal, before digitization process, otherwise the actual fluctuations are not present in the digitized signal of EMG signal which is generated from the activity of MUs. Amplifiers of high input impedance are required for surface EMG. This reduces the noise and interference caused by unbalanced impedance in the electrode. Also they have high CMRR, to reject the noise signals from surface electrodes [8].

A signal is made up of combination of sinusoids having different frequencies. The range of sinusoids for surface EMGs are from 20 Hz to 500 Hz. If sampling is done at the smaller rate that the twice of maximum frequency present in the signal, then the signals tend to mix with each other. The frequency components which have higher frequency than this, are superimposed on the components of lower frequencies, which is called aliasing. Aliasing can be reduced by using low pass filters (block 3 in Figutre 1.2). Another way of removing undesirable parts from surface EMG is to digitize the signal by using digital filters [11]. In digital filters for surface EMG, band-pass filters with cut-off frequencies 20 Hz and 500 Hz are used [9] .

Resolution of the A/D converter is the another matter to acquire the surface EMGs (block 4 in Figure 1.2), generally used for low level contractions. In digitization of amplitude of analog signals, the voltage levels depend directly on the resolution. The resolution of A/D converters is the division of its dynamic range by its number of levels. The number of levels N is given by $2^B = N$, where B is the number of bits.

1.5 Objectives

1. Development low cost and multichannel EMG data acquisition system.
2. Collecting data from at least 12 subjects (both male and female) for different Arm activities.
3. Extracting different Features (Time Domain and Frequency Domain).
4. Reduction of Features to further improvement the accuracy of classification.
5. Applying different classifier to obtain the best accuracy of the different activities.

1.6 Brief Methodology

A multichannel low cost EMG data acquisition system has been developed. For the validation of this system data is taken for arm activities of 12 subjects (male and female). A GUI for displaying real time data has been designed. Further soft computing techniques have been utilized for the classification of the different arm activities. Total seven kinds of activities have been performed by each subject, in the data acquisition approach 5 channels have been taken out of 8 available channels.

1.6.1 Development of low-cost EMG data Acquisition system

A system for EMG data acquisition has been developed, Which is based on ADS1298 IC. It has 8 channels and variable sampling rate from 500 Hz to 32k Hz and 24 bit resolution for analog to digital conversion.

1.6.2 Data Acquisition of Arm Muscles

For the validation of this sytem data base have been prepared for different Arm activities. For this purpose 12 healthy subjects have been choosen of age between 20 to 24. Total 5 channels have been taken for data acquisition.

1.6.3 Real time Display

A real time displaying application has been created in the processing platform. In this Application number of channels for the acquisition display can be manipulated. Data can be saved in desirable format.

1.6.4 Data Analysis and filtering

For the data analysis and filtering purpose MATLAB 15a software were utilized. A band pass filter of frequency range 20 Hz to 500 Hz was used for the noise reduction.

1.6.5 Feature Extraction of EMG data

For the feature extraction both time domain and frequency domains have been considered. Total 10 features have been extracted from each channel (6 in time domain and 4 in frequency domain).

1.6.6 Classification for Pattern Recognition

For the comparative study four types of classification algorithm have been selected (Random Forest, Decision Tree, Linear Discriminant Analysis, Support Vector Machine). The block diagram for the proposed methodology is shown in the Figure 1.3.

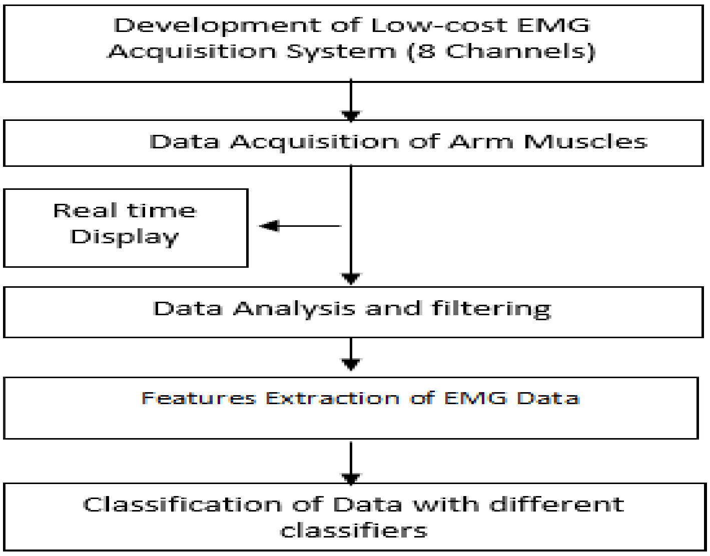

Figure 1.3 Flowchart of Proposed methodology

1.7 Dissertation Organization

Chapter I introduces the basis of EMG signal and understanding of basic architecture of EMG signal acquisition system. It briefly describes the main parts of EMG acquisition system and brief methodology also presented.

Chapter II introduces important researches which have been done in this area. It gives a brief idea about important references, methodology used and the results of that particular research. Gaps in study are also discussed in this chapter.

Chapter III gives a brief idea about the Material and Methods used to develop the complete EMG data acquisition system and protocol for data acquisition. EMG data pre-processing along with main part of the system also discussed.

Chapter IV gives detail about classification algorithms and feature extractions used in this work along with feature reduction.

Chapter V in this chapter, the results and discussions are presented.

Chapter VI conclusion of this study and future scop are presented.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Electromyography (EMG) signals are becoming continuously more important in many areas, including biomedical/clinical, prosthesis, HMI (Human machine interface) and rehabilitation devices. Due to its undesirability to drive display and monitoring system, it needs an adaptable and robust enough processing units to clearly picture the signal.

2.2 Technological aspects

Sang Hui park *et al.* [17] presented an EMG method which recognized pattern to detect the movement instructions to control prosthetic arm with the help of artificial intelligence based accumulation method. Various feature factors like variance, absolute value, linear cepstrum coefficients, auto regressive model coefficients and adaptive cepstrum vector were being extracted. The technique used was evidence accumulation, it used the distance that is measured with reference parameters. Distances are transformed using fuzzy logic.

Zhaojie Ju *et al.* [18] proposed the technique of feature extraction and classification of non linear features and evaluated it. Classification id performed to detect different hand changes based on sEMG i.e surface electromtography. Non linear results were achieved that were based on recurrence plot that represents dynamic characteristics during the movement of hand. The model proposed was fuzzy Gaussian mixture. Different experiments were conducted to determine their performance by making a comparison between 19 multifeature, 14 individual features & 4 different classifiers. Results showed that the technique proposed was good in multifeatures. LDA, SVM, FGMM & guassian mixture model classifiers were used out of which Fgmm outperformed with the accuracy of 96.7%.

Rubana H. Chowdhury *et al.* [19]described EMG signals. EMG signals are very important in almost all applications including prosthetic devices installation, biomedical field, human machine interactions and many more. But noisy EMG signals decrease the performance, so these noises were being detected and classified. Possible artifacts were being eliminated by pre processing. Different methods were proposed for processing and classification. Performance was analyzed.

Donald E. Geister *et al.* [20] designed a data acquisition system based on computer, to digitize EMG signals & jaw movement data set. Significant number of patients, efficient acquition & short analysis times were required. Real time capability was used to adapt high speed data collection from multiple signal sources that were biting force, 5 EMG channels & jaw position. The digitized data was also reduced for the presentation purpose. This provided better dental treatment.

Stefano Di Pascoli *et al.* [21] designed a system to record EMG and ECG signals of birds and mammals, for activity of brain. Chicken embryos were the subjects in this study. The system was attached to the subject through out the whole process. Electrode wires were implanted on the heads of embryo & transmitter was connected to those electrodes. It had maximum sampling frequency of 500hz, 6 channels & 12 bit resolution. Receiver transmitted the data from PC to transmitter. Microprocessor was also used to perform various operations.

James M. Dzierzanowski *et al.* [22] described the execution of knowledge based system to evaluate abnormal human motion arising from CVA. GAITSPERT system was used, it had knowledge about the judging of human gait as a clinical tool. Bio medical signal acquition , artificial intelligence & intelligent processing like EMG, kinematic & foot switch data set were parts of GAITSPERT. It was general purpose engineering tool of knowledge.

Christodoulos I. *et al.* [23] described about the diagnosis of neuromuscular disorders by fetching the EMG and MUAPs bio signals. Recognizing MUAP, then classifying similar shaped MUAPs, then decomposition of superimposed MUAPs methods were presented to extract information for disorders. Classification of MUAPs was done using two different techniques, a statictical pattern recognition method based on distance and second was an artificial network method. 1213 MUAPs were obtained from 12 normal persons, 15 suffering from neuron disease and 13 suffering from myopathy. Accuracy of ANN was 97.6% and 95.3% for statistical method.

Paolo Bonato *et al.* [24] analyzed the lower back pain by analysing sEMG signals collected from the back muscles. Before this, extension of this method was not feasible for different tasks like lifting, as due to non stationary EMG. Various methods like IMDF & time frequency analysis methods were used to overcome such limitations. Data set was obtained during lifting task of 9 subjects. There was a significant decrease in IMDF, among contralateral muscles and lower lumbar region data sets were greater decreased. Acceleration was increased.

Rodrigo Licio *et al.* [25] proposed that myo-electric signals can also be used to control systems e.g. artificial neuro-muscular simulation and prostheses. These systems were used in all types of environments & different noise levels were analysed on this system. Noise reduction methods that were evaluated were adaptive digital filters, wavelet transform 7 non adaptive filters. The signal was reconstructed using wavelet excluding noise signals. LMS and RLS methods were being used to design adaptive filters.

Maria Chiara *et al.* [26] presented an investigation of mechatronic systems, using subjects foot movements. Pressure variations were recorded by sensory system. Prototype was developed which combine battery, sensitive areas & electronics. Use of electronics was wireless transmission & data acquisition purpose. Comparison between trials was done and showed that there was a decrease in required adaptation.

Refet Firat *et al.* [27] demonstrated the increasing demand for small size, low power and ambulant biopotential systems. This paper implemented a low noise and low power readout with configuration characteristics for ECG, EMG, EEG signals. ACCIA (AC coupled chopped instrumentation amplifier was used which has low power consumption. Chopping filter was used to remove the input chopper spikes of ACCIA and gain was set by variable gain stage.

Siti A. ahmad *et al.* [28] proposed a technique for extraction information from sEMG. Tasks that were performed were ismetric contractin, wrist flexion/ extension and co-contraction and EMG signals were obtained using surface electrodes. In this study 200 values window moving data was applied to data set. There was regularity in EMG signals when contraction was done during middle part.

Kahori Kita *et al.* [29] proposed a technique to generate traning data using a clustering method that was self organized and later EMG signal classification was performed. EMG signals were collected during the movement and then feature extraction was done based on patterns of EMG signals. Connections between these movements and feature paterns were analyzed and training was being done. Accurate thresholds were determined to determine the feature patterns.

Yanjuan Geng *et al.* [30] described EMG recognition methods with amputees (to control multifunctional prostheses) and able bodied subjects. These had high performance in detecting different motions. When movements were referred to single joint, it was not clear that whether the functional tasks that were performed, involved in hand & arm could be differentiated using EMG based pattern methods. EMG signals were classified in 8 functional movements and no movement was also included to it. Auto regression model, time domain, features, wavelet coefficients, TD & AR features were being used for the representation of EMG patterns. The classification accuracy of TD features was came out to be greatest i.e. 94%.

Edoardo Fiorucci *et al.* [31] evaluated muscle activity & stress like facial muscles. Surface EMG was used to evaluate the activity of human surface muscles with non invasive methods, although it was not an easy task because of low S/N ratios. Surface EMG signals were obtained to increase the ratio S/N. Filtering and amplification was done during this research. The aim of this paper was to propose a new system which can process and acquire the EMG signals in rest. In this study it was achieved by designing a prototype.

Taro Shibanoki *et al.* [32] introduced a channel & motion selection method. The basis of selection was Kullback Leibler information. Probability density functions were estimated. Neural network was also used for probability density function determination. Classes and dimensions were selected by reducing ineffective data. Classification motion was chosen when channel selection had been done.

Ali Ekber Ozdemir *et al.* [33] compared the classification techniques. The aim of the study was to put forward a viewpoint that was related to choice of features for EMG controlled prostheses development. Features were obtained from the data set by using time frequency domain transformation and time domain transformation. It was described that according to the previous study, the signal processing time period would be less than 300ms.

Jose Antonio *et al.* [34] described about the wearable sensors. It was described in this paper that wearable sensors would be included in the form of biometric or biopotential measurement in the garments. This paper presented ASIC device for acquiring EEG, ECG and EMG data. Different analog filter configurations were compared together. It was not a feasible method for analog filters to adjust to adapt to different bio-potential signals. So ASIC device was being used to measure different types of signals such as EMG, ECG & EEG.

Lukai Liu *et al.* [35] investigated frequency and time based features of the surface EMG obtained from different channels. These signals were used to control upper limb prostheses. EMG based movement classification was the control method that was used in this study. It was proposed that the EMG signal was a processing step in classification. Whitening of EMG signal was considered good as it has advantages over EMG signal. Advantages of whitening are like force processing, amplitude estimation of EMG etc.

Lauren H. Smith *et al.* [36] described that the degrees of freedom is important to control the limbs. The aim of this paper was to determine whether the EMG were comparable to surface EMG signals. 1- DOF & 2-DOF movements were predicted that involved wrist extention/flexion, wrist rotation & hand close/open. Classifier differentiation between 1-DOF & 2-DOF were analyzed along with three classifiers that would predict the activity of 3-DOFs. It showed that the classification error would be decreased by using the intramuscular EMG signals.

Sungtae Shin *et al.* [37] introduced that myoelectric signal could be used as a control signal for amputees to perform their daily life tasks. This paper introduced that a variety of commercial products had been developed that use myoelectric powered controls, but they were still insufficient to satisfy the demands of amputees. Different types of classification methods were studied for comparison purpose. Repeatability, accuracy and robustness parameters were included in this research and seven classification techniques were used. There were five number of feature sets and quadratic discriminant method showed high accuracy, low computational time and high robustness.

Simone Benatti *et al.* [38] presented an embedded system hand gesture recognition that was based on real time EMG. Both hardware and software components were used to design the multi level system. A wearable device was designed in this paper which could acquire and process EMG signal. High performance and low power microcontroller was used. The design that was proposed in this study was compared to wearable devices and better performance was achieved. Accuracy of classification came out to be 90%, power consumption was 29.7 mW.

Abdul Rahman *et al.* [39] developed an articial thumb as almost all tasks are performed by using thumb. Therefore designing an artificial thumb was a major achievement, although it was a challenge to make a thumb exactly lika a human being’s thumb. This study included the classification of EMG signals collected from thumb muscles for predicting force and thumb angle. The experiments were performed to measure the thumb angle and force durin flexion motion, then features were extracted and most relevant and important feature was investigated and applied to some classifiers. Frequency domain features showed better results than the time domain features thus broke away the past researches.

A. P. Vinod *et al.* [40] presented the design of integrated surface EMG acquisition device to measure electric activity of muscles. It measured the explosion power, electrical activity & fatigue degree. The hardware consisted of four units which included signal processing unit, signal detection unit, signal conditioning unit & A-D convertor unit. Extracted parameters & EMG signals were displayed on GUI. Relationship between the muscle activity and tension was validated by an experiment. Results shown were faster response by female subjects where as muscle activity was good by considering male subjects.

N. lelpo *et al.* [41] described that the surface EMG is one of the important signals that could be collected and processed. Useful information were extracted to diagnose and treatment of lower limbs. This paper provided a reliable anf flexible system which allowed the extraction of synthetic parameters in frequency & time domain. EMG miner was also proposed in this paper that allowed automated acquisition. Analysis of emg signals was done along with the different stages of restoration process of a subject. Physical medicine and restoration analysis was done during this research.

Sumit A. Raurale *et al.* [42] performed an experiment to identify the real time EMG signals of hand movements to control prosthetic robotic arm. Efficient exploitation of emg signals was considered as anterior & posterior forearm muscles. In this research work, features were being extracted by statistical time-frequency technique. Further, LDA was used to classify pattern, standard deviation used was (88-91)% ± (0.1-0.3)%.

Kentaro NAGATA *et al.* [43] proposed the technique for classification of hand movements. It included 96 channels matrix-type(16x6) of multi channel surface electrode. This research explained that there were many systems designed for emg signals but definition of measuring position is required in almost every system. So, this research designed the system which did not have these types of problems. Electrode position selection was not necessary.

Hardeep S. Ryait *et al.* [44] performed four operations like griping, opening and closing of hand etc. SEMg amplifier was used which is used to extract myoelectric signals. Signal was acquired from hardware by using Matlab. Total six channels were used to acquire data. Matlab filter algorithm was helpful in interpretation of data acquired from six channels. Best emg signal was selected by PCA technique. In this research work, two points were also selected on the wrist along with the other points. Research work showed that SEMG is very helpful in prosthetic hand.

2.3 Gaps in the study

In the previous work the proposed designs for EMG data acquisition are based on Instrumentation amplifiers. One instrumentation amplifier requires for one channel data acquisition, this makes circuitry complex and provide time delay in signal processing. Several expensive system are also available in the market but they are out of reach for the research in comman laboratory. Creating an improved and cheap device that can overcome these obstacles is essential for this research work.

CHAPTER 3

MATERIAL AND METHODOLOGY

3.1 Introduction

EMG signals are very important in almost all applications including prosthetic devices, biomedical field, human machine interactions and many more**.** Limited bandwidth of electric potentials lie within 20 to 500 Hz and its amplitude ranges from 50uV to 20-30mV peak-to-peak, it depends upon the intensity of muscle contraction [9]. Signal detection is done at first, further amplification part is done, then comes the conditioning and digitization of surface EMGs.

3.2 Hardware Development

Common acquisition systems of EMG signals are established on following main pieces:

1. Electrodes
2. Differential Amplification
3. Filtering Process
4. Analog to Digital conversion
5. Digital Signal Processing
6. Display Unit

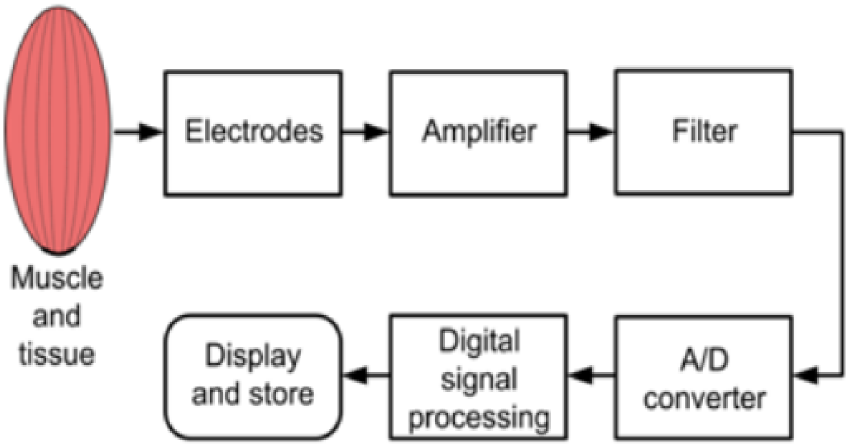

Figure 3.1 Block diagram of EMG Acquisition System

Electrodes act as the interface between muscle tissue and EMG signal amplifier. In the implimented system above mentioned important parts (Differential Amplifier, Filtering, Analog to Digital coverter) of acquisition system are in a single. Development of this EMG acquisition system is based on ADS1298 IC shown in Figure 3.1.

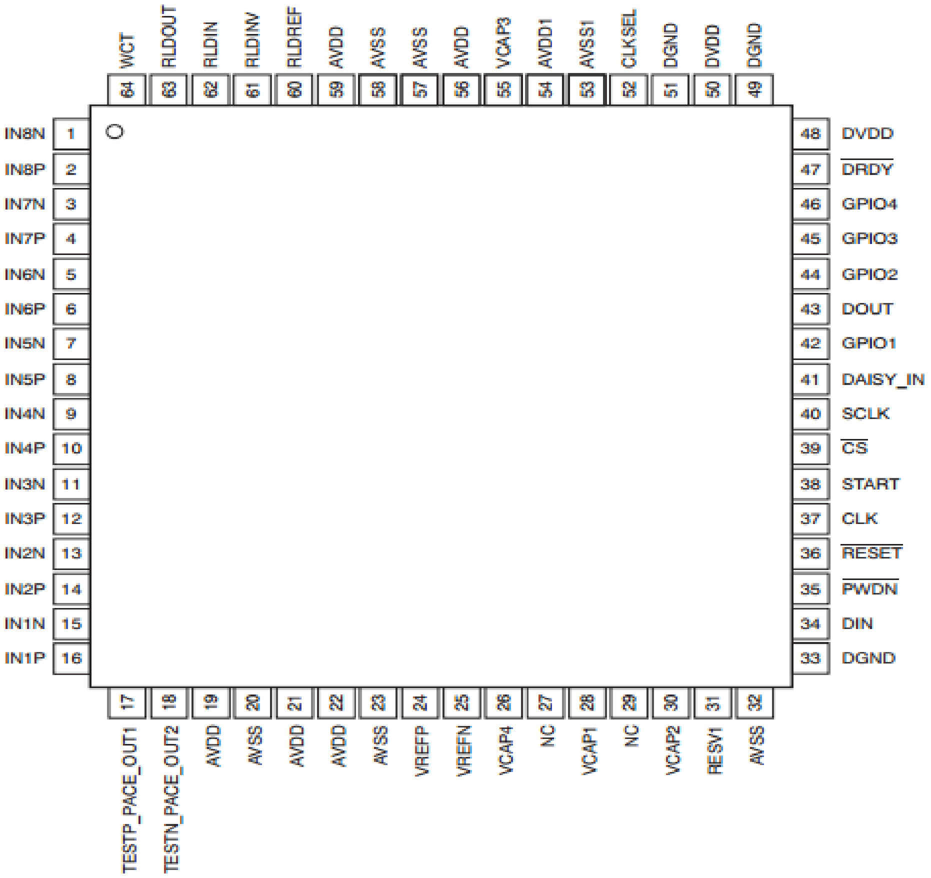

Figure 3.2 Pin diagram of ADS1298 IC

3.3 Features of ADS1298

1. 8 low noise Programmable gain Amplifiers (PGA) and 8 high resolution ADCs (Analog to Digital converters).
2. Low power consumption (0.75mW/channel).
3. Variable Data Rate 250 SPS to 32000 SPS with CMRR -115dB.
4. Programmable Gain :1,2,3,4,6,8 or 12.
5. Power supply: Unipolar and Bipolar
    a. Analog: 2.7 to 5.25
    b. Digital: 1.65 to 3.6V.

6. SPI interface (compatible Serial interface).

Before each input, it owns a second order passive low passfilter of 1k Hz cut-off frequency and schottky diode protection circuit shown in Fig.3.2, by using 2nd order low pass filter aliasing is removed and with the help of schottky diode combinations, the signal that is below maximum voltage will be allowed to pass, the rest voltage will be passed through schottky diodes. Schottky diode has high switching speed so that only unneeded voltage will be passed through it. Further teensy 3.2 module of is used for decoding of SPI data.

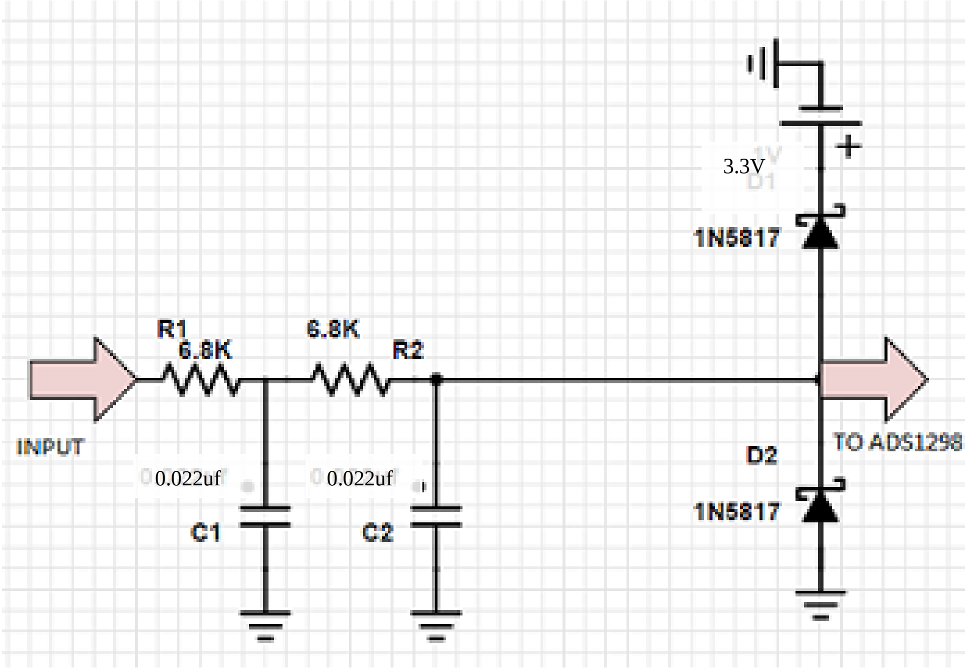

Figure 3.3 Protection circuit

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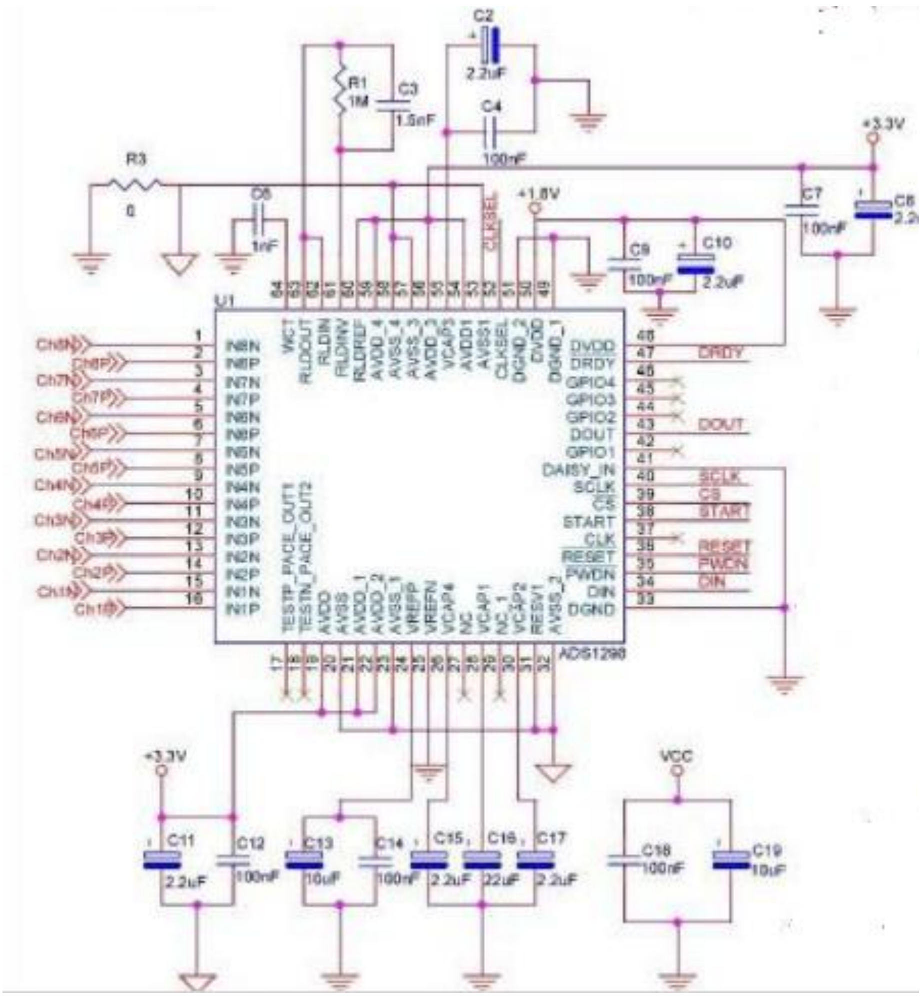


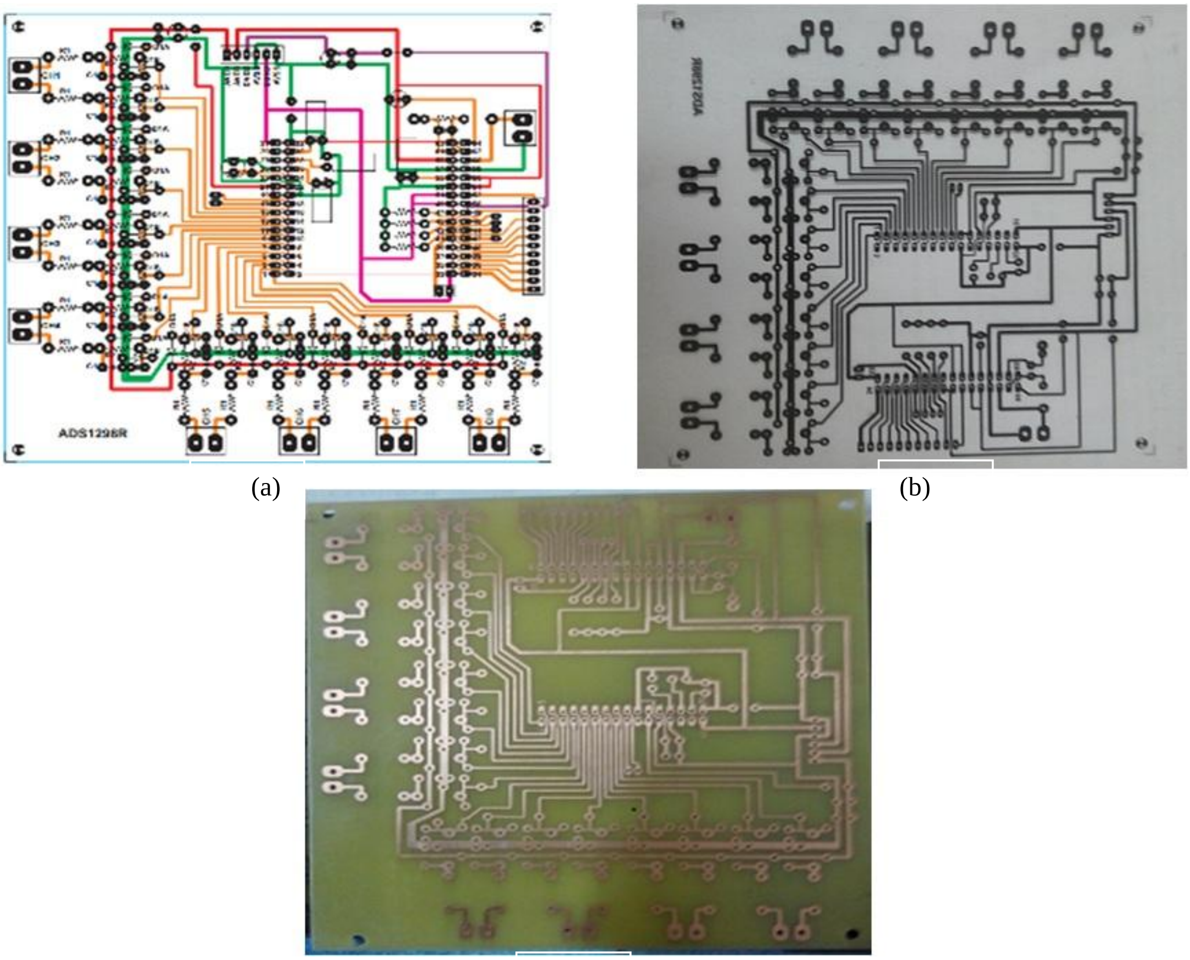
Figure 3.4 Circuit Diagram of ADS1298 IC connections

3.4 PCB Development and System Demonstration

After designing Schematic of the circuit the main task is to develop PCB for that circuit. There are mainly three types of PCB designing techniques.

1. Single sided PCB
2. Double sided PCB
3. Multi layer PCB

The single sided PCB designing is cheap as compare to other types of PCB designing techniques but system or circuit will become bigger (wide) than the multi-layer PCB design. In this work the Single sided PCB has been taken to develop or implement our circuit on to the Copper plate for reduction of the size of the circuit shown in Figure 3.5.



(a)

(b)

(c)

Figure 3.5 Circuit Designing Process: (a) Layout of Circuit (b) Film of PCB (c) Drilled PCB

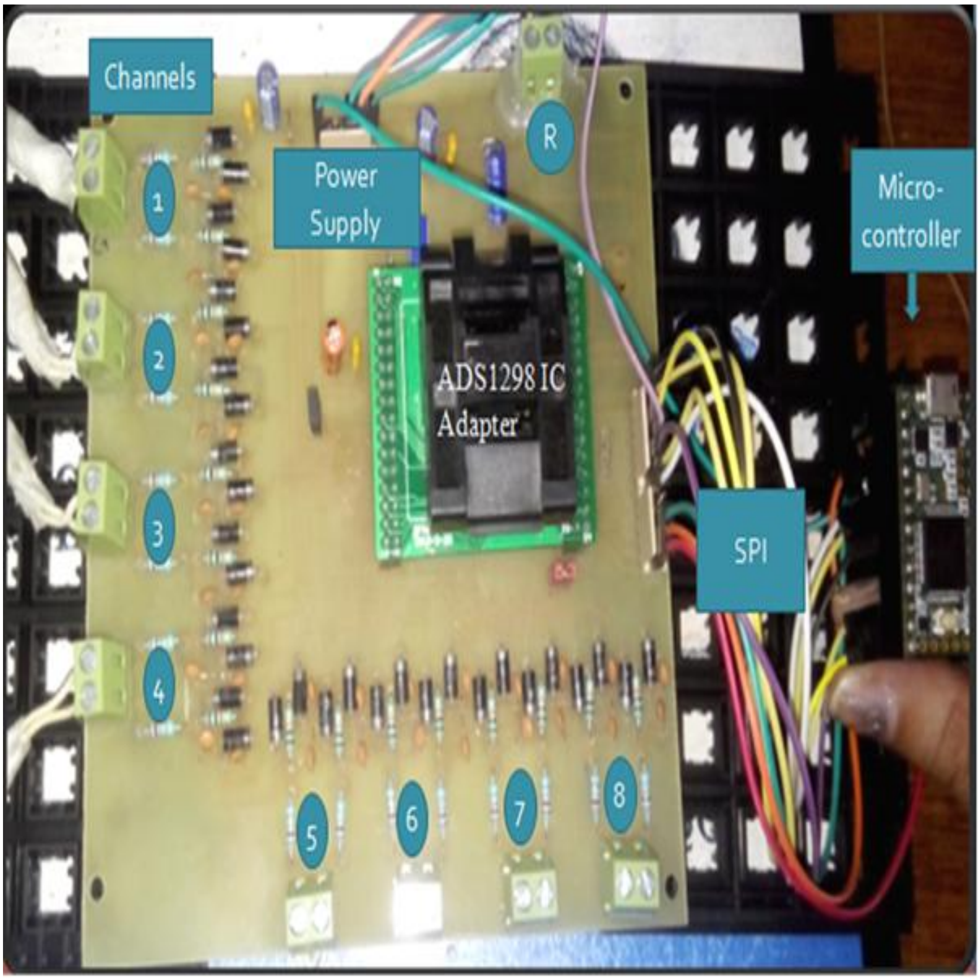


Figure 3.6 Proposed EMG acquisition system

The ADS1298 IC has TQFP package so a TQFP to DIP converter or IC adapter have been used as shown in Figure 4.4.

The GUI has options to manipulate sampling rate, number of channel (from 2 to 8 channels), data save or not. For making this GUI the processing software is utilized.

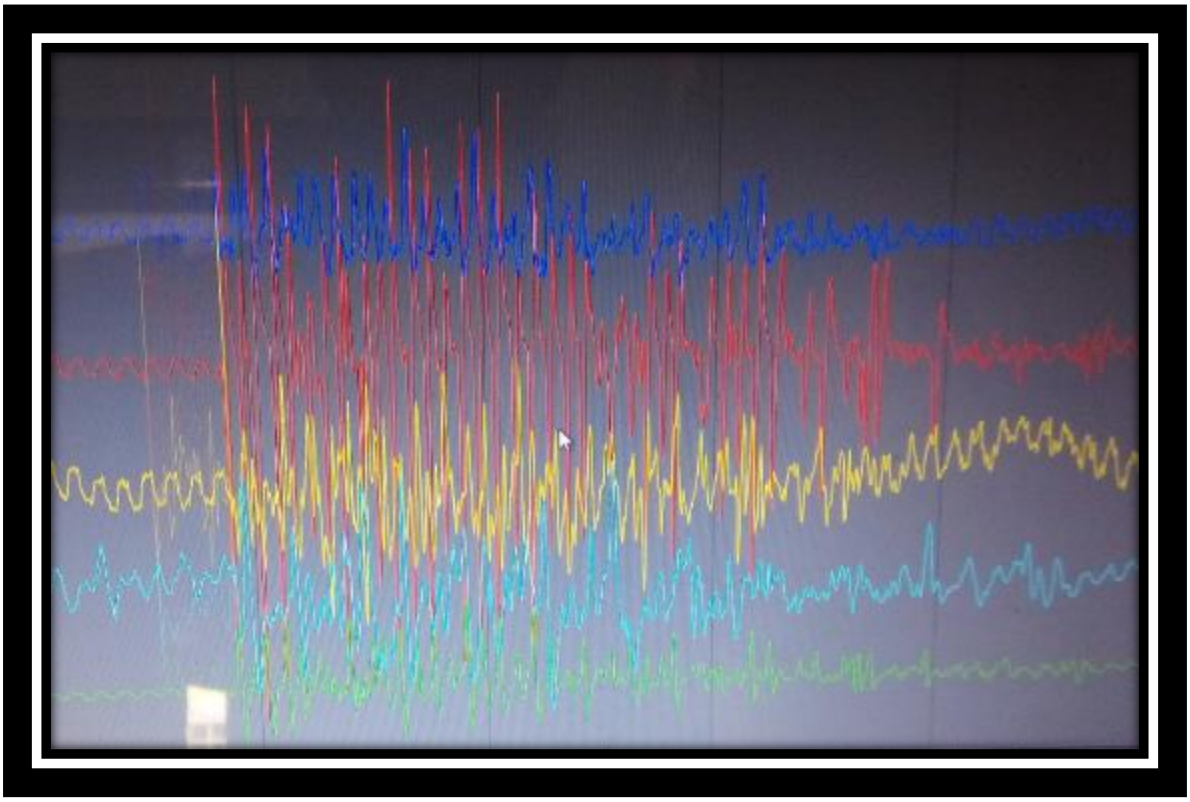


Figure 3.7 Real time data Display of 5 channels

3.5 Electrode placement and Protocol for Data Acquisition

Orientation and the location of muscles are the main factors which affect the strength of the signal acquired from the skin surface. The placement of electrodes should be in between the tendinous insertion and motor unit of the muscle. It should be placed along the longitudinal midline of the muscle [15]. The longitudinal axis of the electrodes (which passes through both detecting surfaces) should be parallel to the length of the muscle fibres. Belly of the muscle has been proved as the best location. Here, the density of target muscle fibre is the highest [16]. Figure 3.8 shows the proper EMG electrode placement. There is more cross section of same muscle fibers which gives the better superimposed signal.

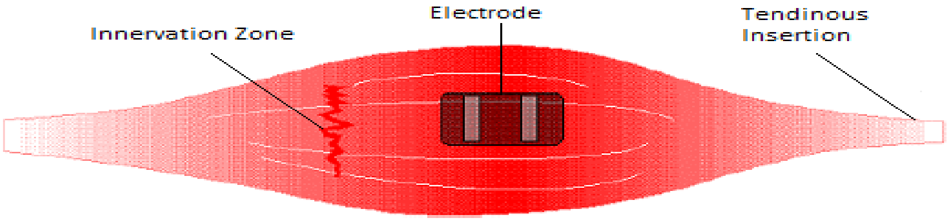


Figure 3.8 The ideal position of the electrode: (two detecting surfaces) is between the innervations zone (or motor unit) and the tendinous insertion (or belly of the muscle)

3.5.1 Reference electrode placement

All the EMG signal from surfaces are combined with respect to a reference signal. An EMG reference electrode acts as a ground for this signal. The placement of an electrode should be far from the EMG detecting surfaces and should be located on an electrically neutral tissue [17].

3.5.2 Protocol for data Acquisition

To acquire the EMG signals more accurately, the impedence of skin should be less. So, the skin of subject should be cleaned before acquition of EMG signal. Dead skin cells and hairs must be removed from the skin surface. For this, abrasive gel should be used to remove the dead skin [3]. Also moisture content can weaken the signal, so there should not sweat drops on the skin. Main procedure that has been carried out for acquition of signal from surface is described below:

a) Five channels have been chosen out of eight channels that are available in hardware.
b) Data have been collected from 12 subjects of age between 22 to 26 (8 males and 4 females), total seven activities are performed by each subject.
c) The EMG database has been collected by performing 5 positions of the right arm using bipolar Ag/AgCl electrodes (H124SG, KendalARBO) [3]. Muscles positions of electrode placement are:

Table 4.1 Muscles for EMG signal Acquisition [14].

S.No.	**Muscles**	**Channels**	**Muscles Name**
1.	M1	(Channel 1)	Extensor Carpi Ulnaris muscle
2.	M2	(Channel 2)	Extensor Digitorum Communis muscle
3.	M3	(Channel 3)	Extensor Carpi Radialis Longus muscle
4.	M4	(Channel 4)	Flexor Farpi Radialis muscle
5.	M5	(Channel 5)	Biceps Brachii muscle

d) Each activity is performed five times after training the subject. Training has been provided for reducing cognitive effect.
e) The EMG data has been collected from the volunteers, performing seven upper-limb actions HO (Hand open), HC (Hand closed), WE (Wrist extension), WF (Wrist flexion), SG (Soft gripping), MG (Medium gripping) and HG (Hard gripping) shown in Fig 5.

f) A band-pass filter of 60–500 Hz bandwidth and an amplifier with 12x gain were used. Sampling frequency was set at 4000 Hz.

g) Then overlapped windowing technique was applied for segmentation of EMG signal, window size was taken 300ms with window shift of 0.032ms [6].

For the data prepossessing and data classification MATLAB 15a software is used.

Figure 3.9 Performed Activities: (a) Hand open (b) Hand close (c) Wrist flexion (d) Wrist extension (e) Soft gripping (d) Medium gripping (e) Hard gripping

Figure 3.10 Gripping activity of 1 subject

CHAPTER 4

FEATURE EXTRACTION & CLASSIFICATION

4.1 Introduction

Because of the various artifacts and noises detected among EMG signals, required information remains merged inside the raw EMG signals. The use of these type of signals decreases the classifier’s efficiency. Different EMG features is being used by the scientists to increase the accuracy. To achieve optimum classification performance, the properties of EMG feature space (e.g., Maximum Class separatability, robustness, and the computational complexity) should be taken into consideration [12]. Data processing and classification process is shown in Figure 4.1. In this paper two feature groups, which are defined in the time domain and frequency domain, have been considered. Total ten features, six-time domain and four frequency domain features are examined shown in Table 4.1

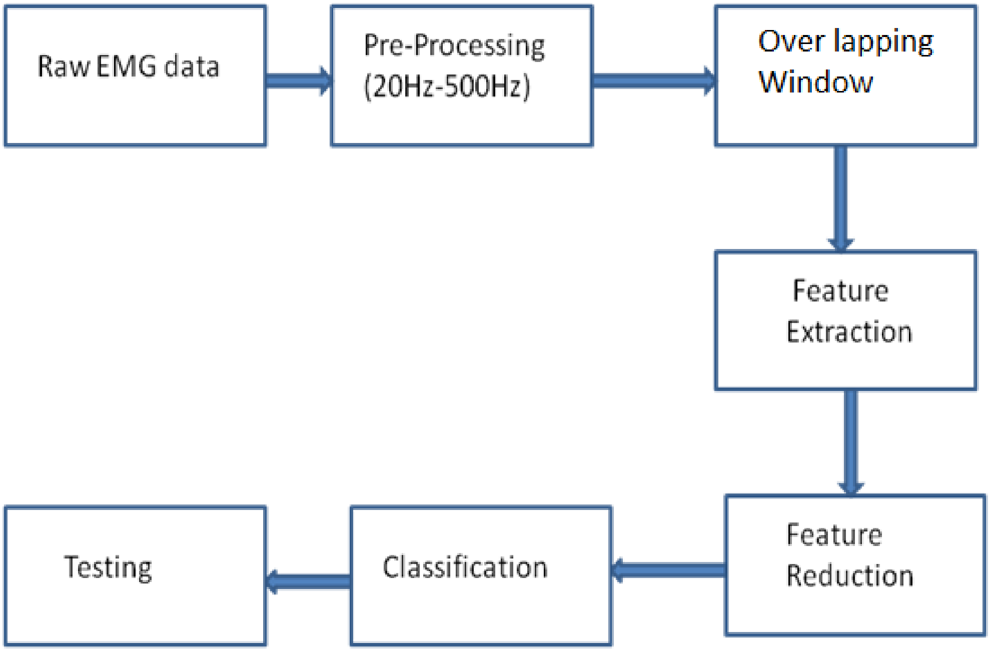


Figure 4.1 Block Diagram of Feature Extraction and Classification Process

Table 4.2 Features examined

Integrated EMG	$\mathrm{IEMG} = \sum_{i=0}^{N} \lvert \mathrm{x_i} \rvert$ Where xi denotes the EMG signal in a segment ‘I’ and ‘N’ represents the length of the EMG signal.
Mean Absolute Value	$\mathrm{MAV} = \frac{1}{\mathrm{N}} \sum_{i=0}^{N} \mathrm{w_i} \lvert \mathrm{x_i} \rvert$
Root Mean Square	$\mathrm{RMS} = \sqrt{\frac{1}{N} \sum_{i=0}^{N} x_i^2}$
Waveform Length	$WL = \sum_{i=1}^{N-1} \lvert \mathrm{x_{i+1}} - \mathrm{x_i} \rvert$
Zero Crossing	$ZC = \sum_{i=1}^{N-1} [\mathrm{sgn}(\mathrm{x_i} \times \mathrm{x_{i+1}}) \cap \lvert \mathrm{x_{i+1}} - \mathrm{x_i} \rvert \geqslant \mathrm{T}$ $\mathrm{Sign(x)} = \begin{cases} 1, & if\ x \geqslant threshold \\ 0, & otherwise \end{cases}$
Simple Square Integral	$\mathrm{SSI} = \sum_{i=0}^{N} \mathrm{x_i^2}$
Mean Frequency	$\mathrm{MNF} = \sum_{j=1}^{M} \mathrm{f_j\, P_j} \,/ \sum_{j=1}^{M} \mathrm{P_j}$ Where ‘fj’ is the frequency of the spectrum at frequency bin j, ‘Pj’ is the EMG power spectrum at frequency bin ‘j’, and M is the length of the frequency bin
Median Frequency	$\sum_{j=1}^{MDF} \mathrm{P_j} = \sum_{j=MDF}^{M} \mathrm{P_j} = \frac{1}{2} \sum_{j=1}^{M} \mathrm{P_j}$

Peak frequency Power	$PKF = \max(P_j) \qquad j = 1,2 \ldots\ldots\ldots..M.$
Mean Power	$\mathrm{MFP} = \sum_{j=1}^{M} \mathrm{P_j} \,/\, \mathrm{M}$

4.2 Feature Selection

There are some unwanted features or parameters in the signal, which are not required in the processing, these parameters can be removed by feature selection technique. These are importance to remove as they may decrease the accuracy of classifier. In the proposed work feature selection has been done by two methods:

a) Random forest (Mean decrease accuracy).
b) Manually Channel Selection.

4.2.1 Random forest (Mean decrease accuracy)

This method directly measures the effect of each and every feature on accuracy of the model. There is a calculation of permutation, it measures that how much the permutation decreases the accuracy of the model. The variables which are not important have almost negligible effect on the accuracy whereas, important features contribute significantly to the accuracy.

4.2.2 Manually Channel Selection

In this work, total 5 channels data has been taken for the classification and accuracies for each and every channel have been selected. Best accuracies from channels are combined and other channels have been neglected then again classification is performed. Hence feature selection technique has been performed in this way.

4.3 EMG pattern classification

An efficient means of classifying electromyography (EMG) signal patterns has been the interest of several researchers in the modern era. There are several sorts of classifiers, which are mostly used for different EMG applications, such as:

a) Artificial Neural Network (ANN)
b) Decision Tree
c) fuzzy classifier
d) Linear Discriminant Analysis (LDA)
e) Random Forest
f) Support Vector Machines (SVM)

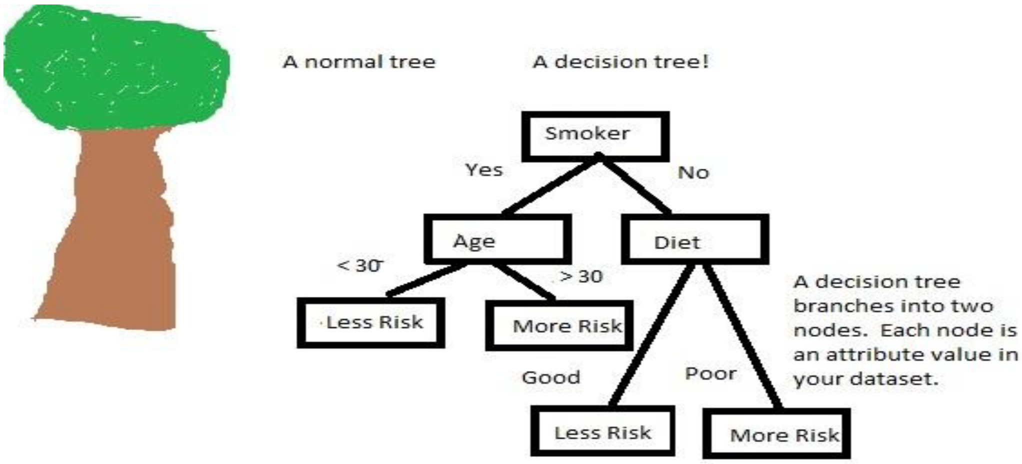
The raw EMG signal is mapped as a feature vector in the feature extraction process, which is applied as an input to the classifier. Because raw EMG signals directly feed to the classifier, they are not practical due to the randomness of the EMG signal. The success of the Electromyogram classification system highly depends on the quality of the selected and extracted features [11]. Feature extraction step in the classification system increase information density of the signal [12].

It is better to classify data with different classifiers instead of a single classifier to understand that, which classifier is appropriate for the machine learning, for comparative analysis and classification of activities. In all types of classification 70% of data is taken as a training data set and 30% is taken as testing data set. Four types of classifiers are used for classification:

a) Decision Tree
b) Linear Discriminant Analysis (LDA),
c) Random Forest
d) Support Vector Machines (SVM)

4.3.1 Decision tree

The Decision Tree is a classification algorithm that classifies a pattern by asking questions, in which the next question asked depends on the answer to the present question [13]. It uses a “divide-and conquer” approach to solve the learning problems [14]. Decision Tree learning methods are one of the most popular inductive inference algorithm. The instances are classified by sorting them down the tree from root to some leaf node which the classification is provided in decision tree algorithms. The attributes of the instance are tested at each node and sent to the sub node or leaf node from one of the branch which correspond the possible values of that attribute [15]. The numeric attributes are tested by comparing a pre-defined constant value at the node and it gives two or three-way split depends on the several different possibilities [14]. Trained trees can be shown by a set of if than rules to increase human readability [15]. An example of three is shown in the Figure 4.2, which is adopted from Quinlan-research.



A decision tree branches into two nodes. Each node is an attribute value in your dataset.

Figure 4.2 Example of Decision Tree classifier

4.3.2 Random forest

Random forest is a tree based algorithm which composed of a number of tree predictors. In this algorithm, each tree is shown by a random vector which is independently taken from the same distribution in the forest. As the number of the tree increase in the forest, the generalization error converges to a limit. The strength of the individual tree and relationship between the trees affects the generalization error. Once all trees in the forest produce a result, they are voted for the most passable class [21]. It is one of the most successful classification methods among the available algorithms for many data type [22], but opposite to other decision tree methods, it makes classification which is difficult to deduce by human.

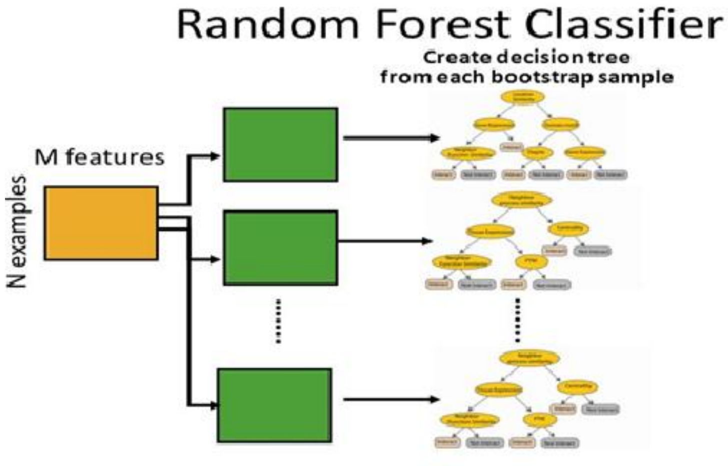


Figure 4.3 Random Forest classifier

4.3.3 Support vector machine (SVM)

It is a type of learning model, which is based on supervised learning. It identifies pattern and evaluates data i.e. used for classification. Although SVM can classify non linear data, but it is suitable for linear data set. Classification in SVM is done by taking the training data of known classes and by separating them into classes [18] . Observations are placed in a space like a point and these are used to classify the unknown new data set. SVM consists of a hyper plane in the space that are used to classify the data set. Higher the margin of the hyper plane from nearest training points of all classes, more good will be the performance of classifier. Figure 4.2 shows the linear classification using SVM.

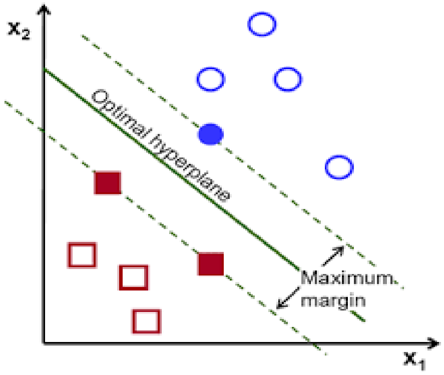


Figure 4.4 SVM classification

4.3.4 Linear discrimination analysis

Linear Discriminant analysis or LDA is a technique which is highly used in pattern recognition, statistics and machine learning. This classifier separates two or more classes of objects or events, linearly. The resulting combination may be used as a linear classifier, or, more commonly, for dimensionality reduction before later classification [15].

It calculates the variance (ANOVA) and regression analysis, in which one dependent variable is expressed as a linear combination of other features. In ANOVA categorical independent variables and a continuous dependent variable are used, whereas in LDA continuous independent variables and a categorical dependent variable are used [15-17]. When it is not assumed that the independent variables are normally distributed, then other methods are preferable to use.

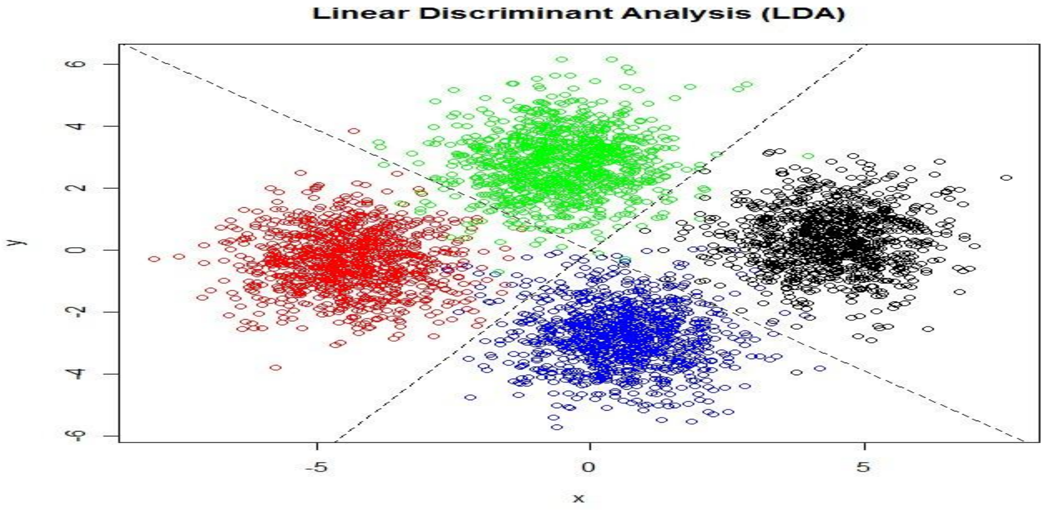
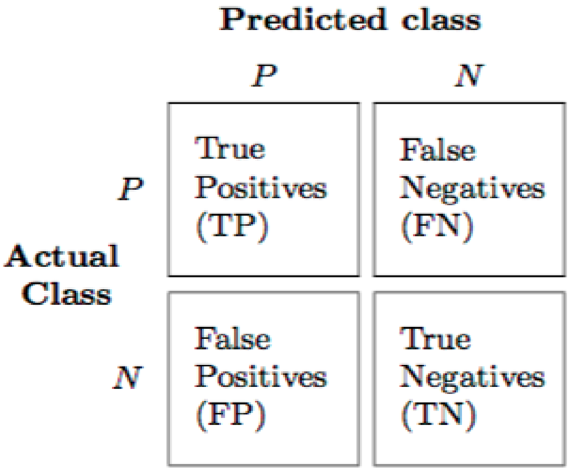


Figure 4.5 LDA classifier

Both LDA and PCA look for linear combinations. LDA works on the difference between the classes of data whereas, PCA does not require the difference of classes.

The result of classification is generally shown as confusion matrix. It is a table which represents the performance of classification. For example, table 4.6 is the example of confusion matrix, where, TP= true positive, FP= false positive, TN= true negative and FN= false negative.



		Predicted class	
		P	N
Actual Class	P	True Positives (TP)	False Negatives (FN)
	N	False Positives (FP)	True Negatives (TN)

Figure 4.6 Confusion Matrix

The main parameters of classification are accuracy, specificity and sensitivity. They are calculated with the help of confusion matrix as below:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4.1}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{4.2}$$

$$Specificity = \frac{TN}{TN+FP} \tag{4.3}$$

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1 Results

This section presents experimental results of developed system. Before Extraction of features of EMG signals first a band pass filter is applied of 60 Hz to 500 Hz range. Butterworth bandpass filter have been chosen of 6th order. In Figure 5.1 raw EMG signal have been presented and then its frequency spectrum has been calculated which is shown in Figure 5.2. It can be easily analyzed that frequency components Varying from 0 Hz to 1500 Hz, time domain signal also showing DC shift. After applying Butterworth band pass filter (20 Hz to 500 Hz), undesirable frequency components have been reduced and its DC shift also eliminated as compare to raw EMG signal shown in Figure 5.3.

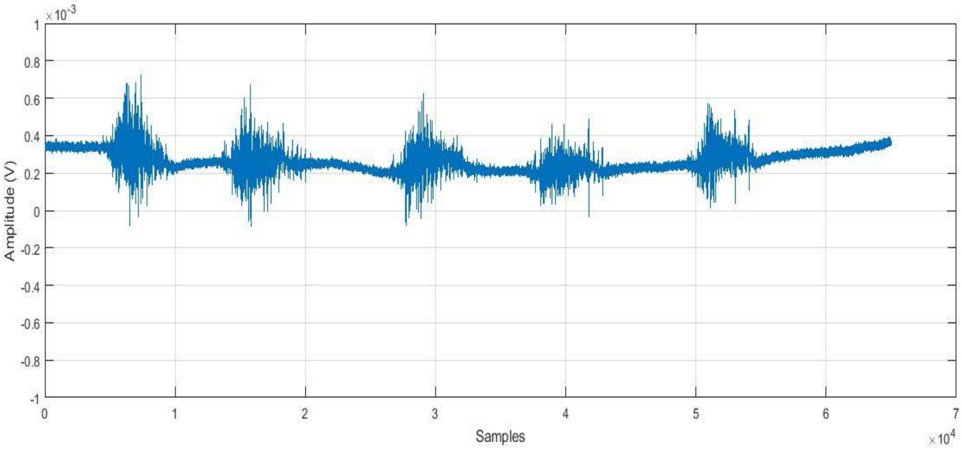


Figure 5.1 Raw EMG signal For Hand close activity channel 1

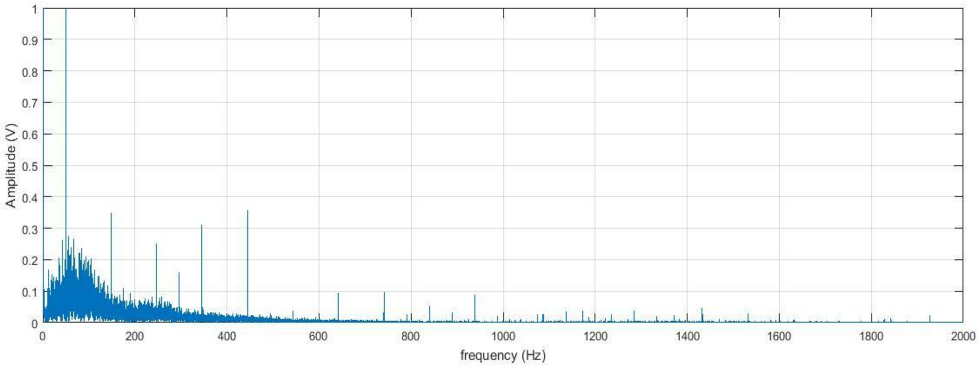


Figure 5.2 Raw EMG signal Frequency Spectrum for Hand close activity channel 1

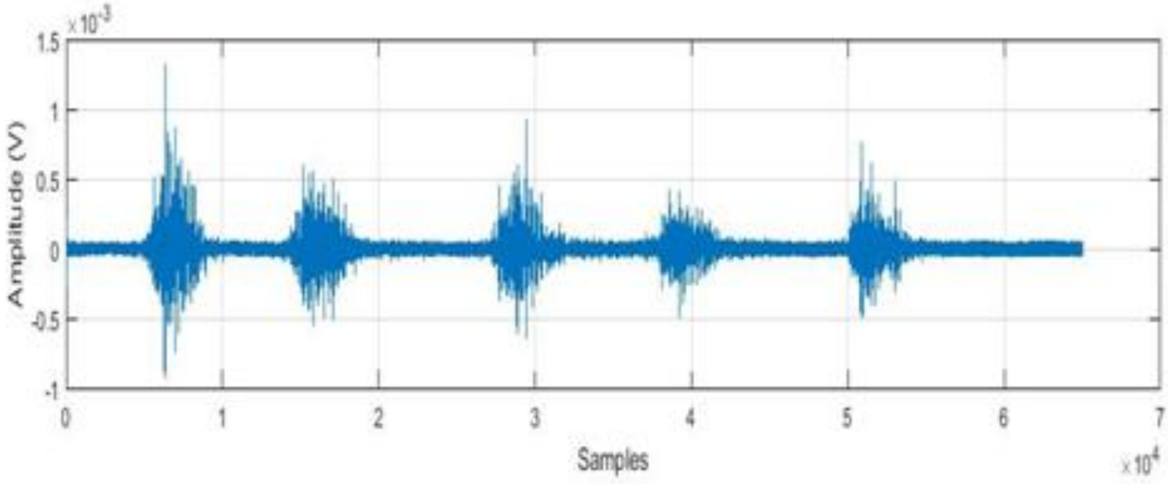


Figure 5.3 Filtered EMG signal For Hand close activity channel 1

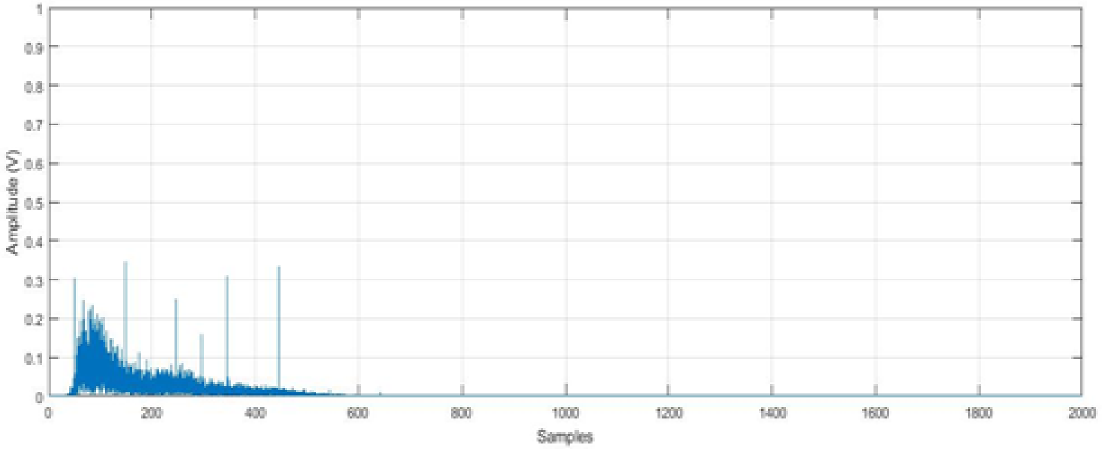
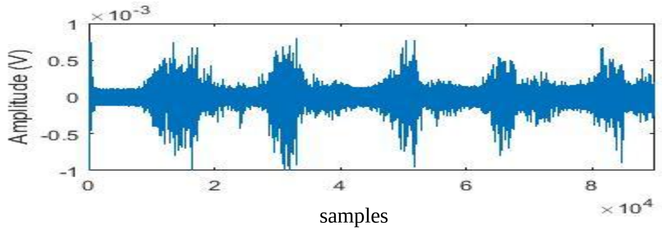
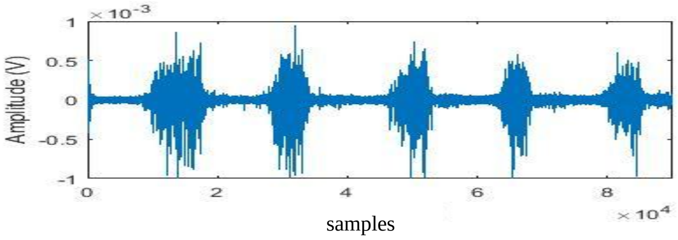


Figure 5.4 Filtered EMG signal Frequency Spectrum for Hand close activity channel 1

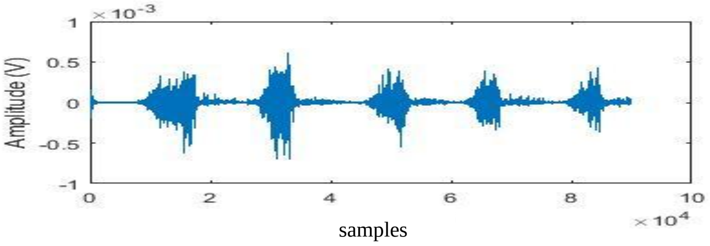
Further each channel's output been have presented for 1st subject. Total 7 activities wave forms are shown Figure 5.5 to Figure 5.11.



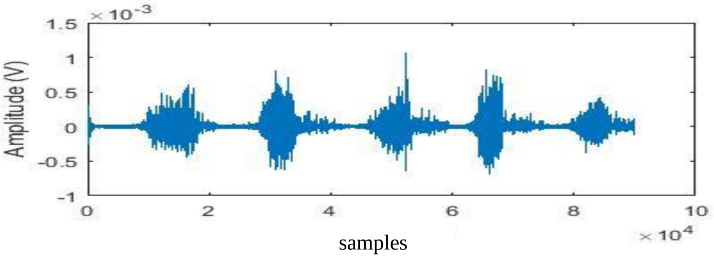
(a)



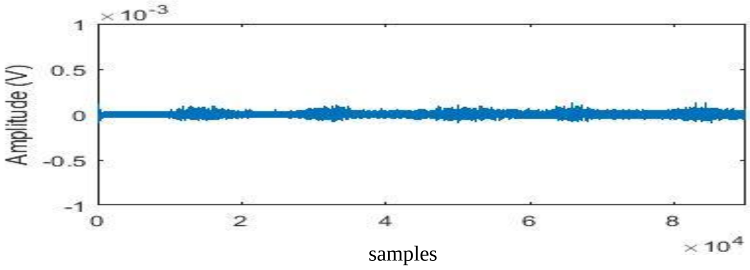
(b)



(c)

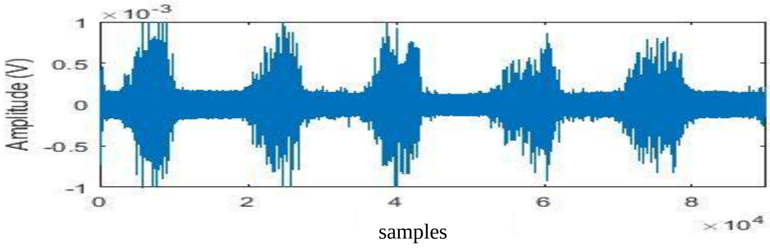


(d)

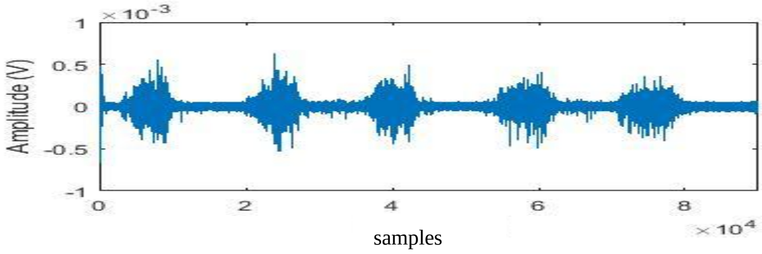


(e)

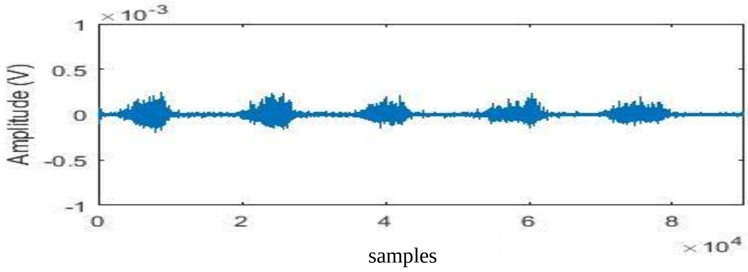
Figure 5.5 Hand close activity wave forms: (a) channel 1 (b) channel 2 (c) channel 3 (d) channel 4 (e) channel 5



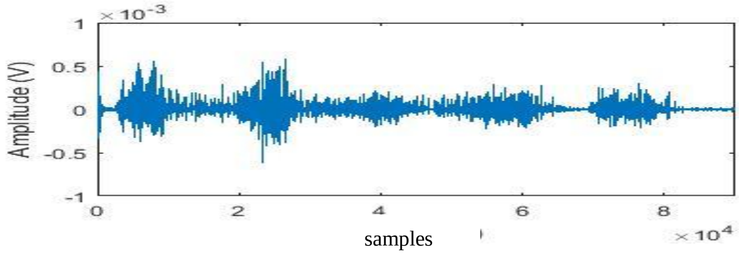
(a)



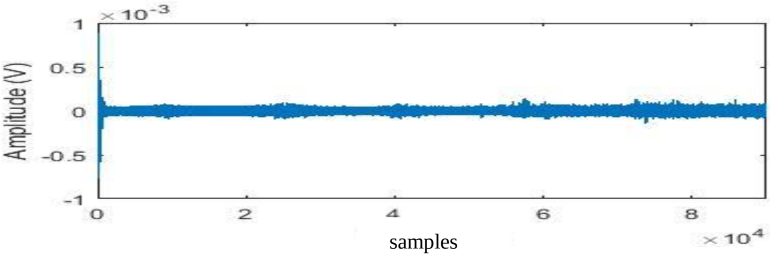
(b)



(c)

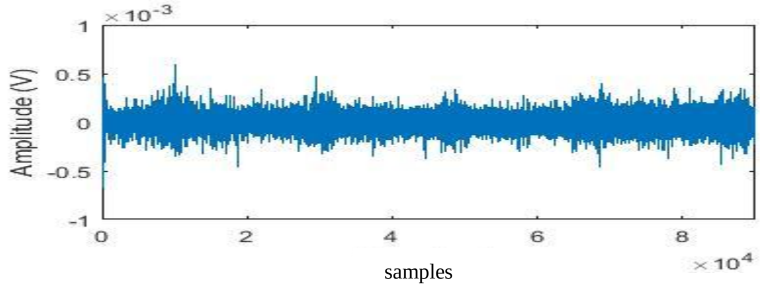


(d)

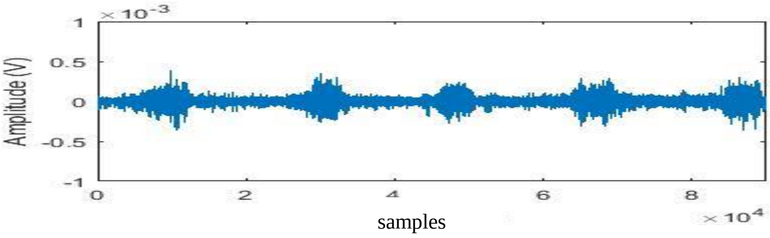


(e)

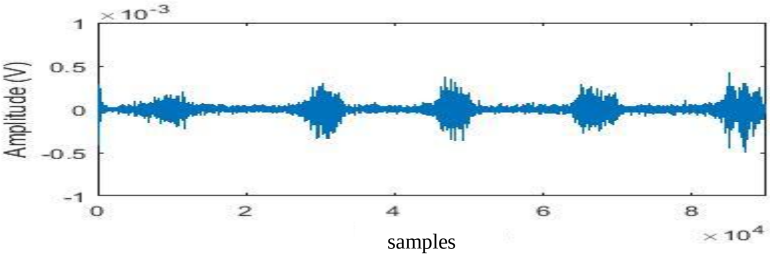
Figure5.6 Hand open activity wave forms: (a) channel 1 (b) channel 2 (c) channel 3 (d) channel 4 (e) channel 5



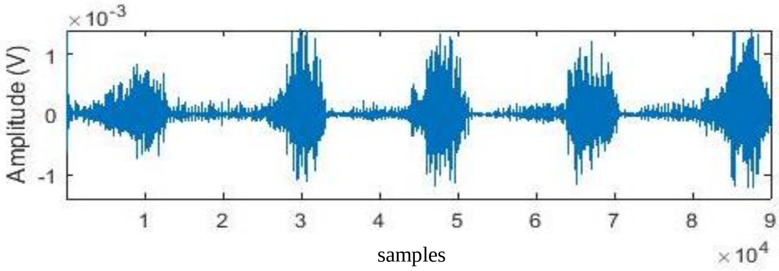
(a)



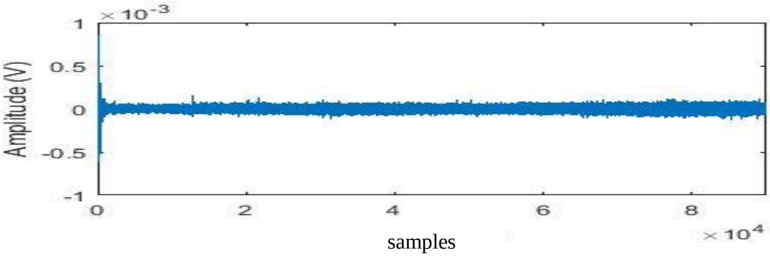
(b)



(c)

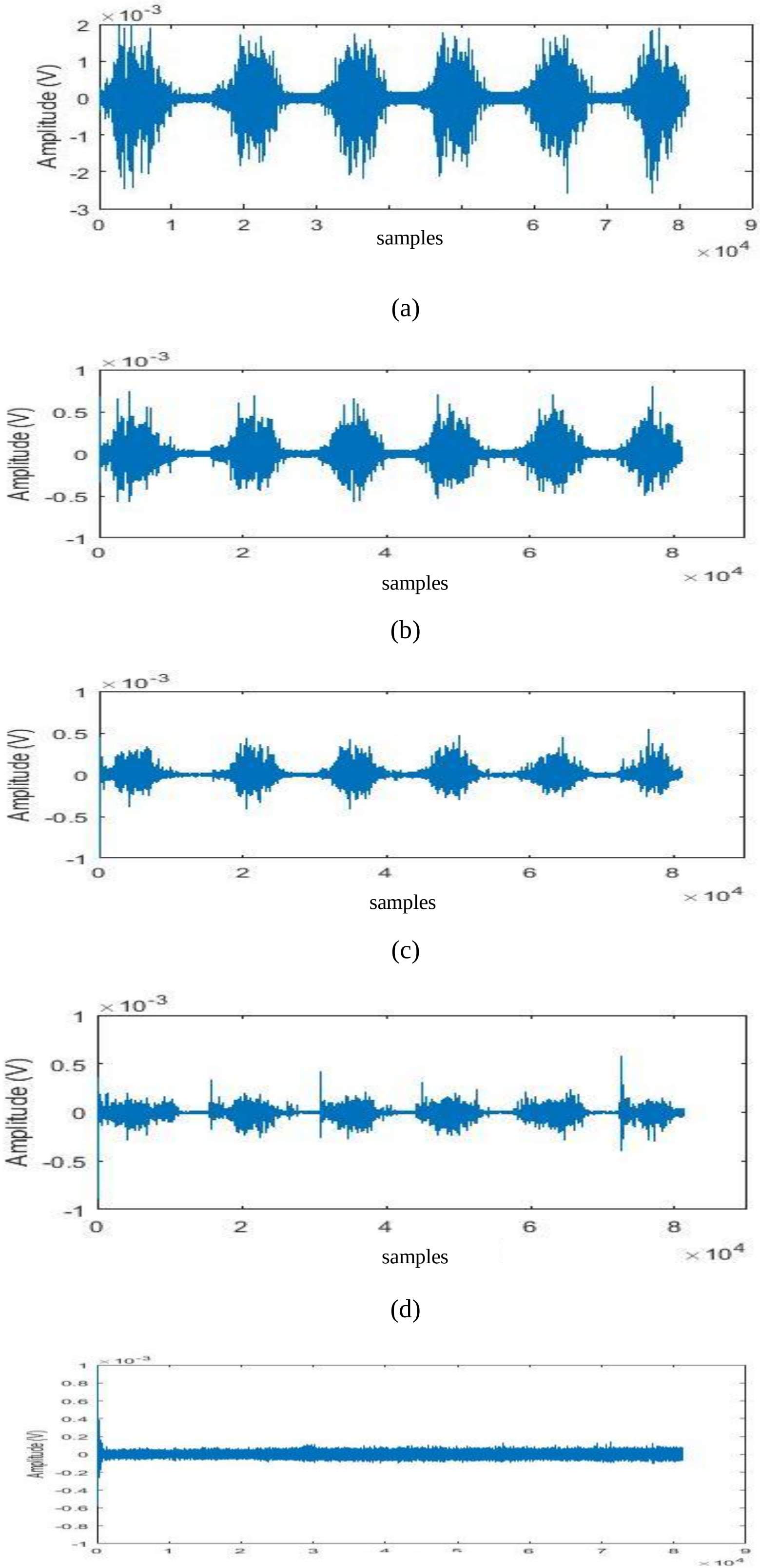


(d)



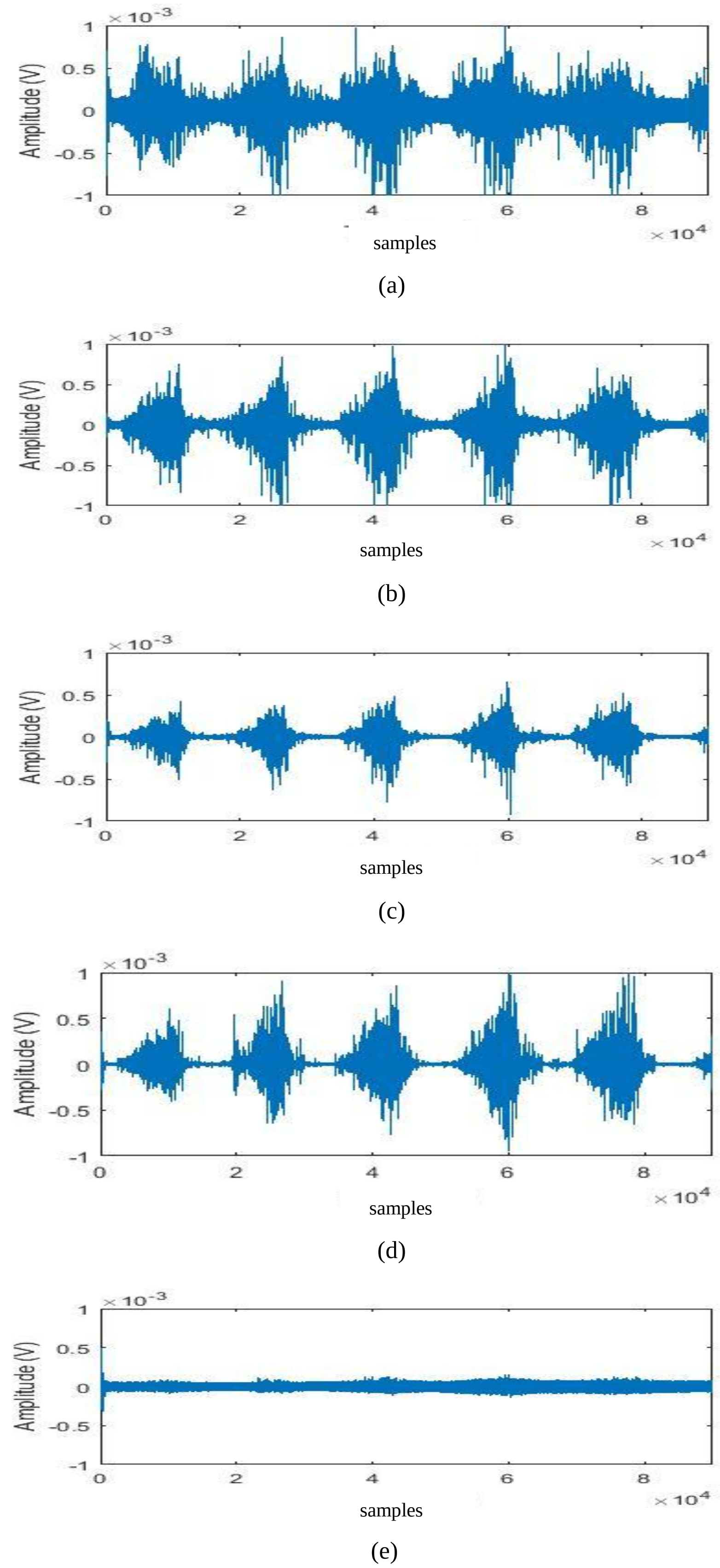
(e)

Figure5.7 Wrist flexion activity wave forms: (a) channel 1 (b) channel 2 (c) channel 3 (d) channel 4 (e) channel 5



(e)

Figure 5.8 Wrist extension activity wave forms: (a) channel 1 (b) channel 2 (c) channel 3 (d) channel 4 (e) channel 5



(a)

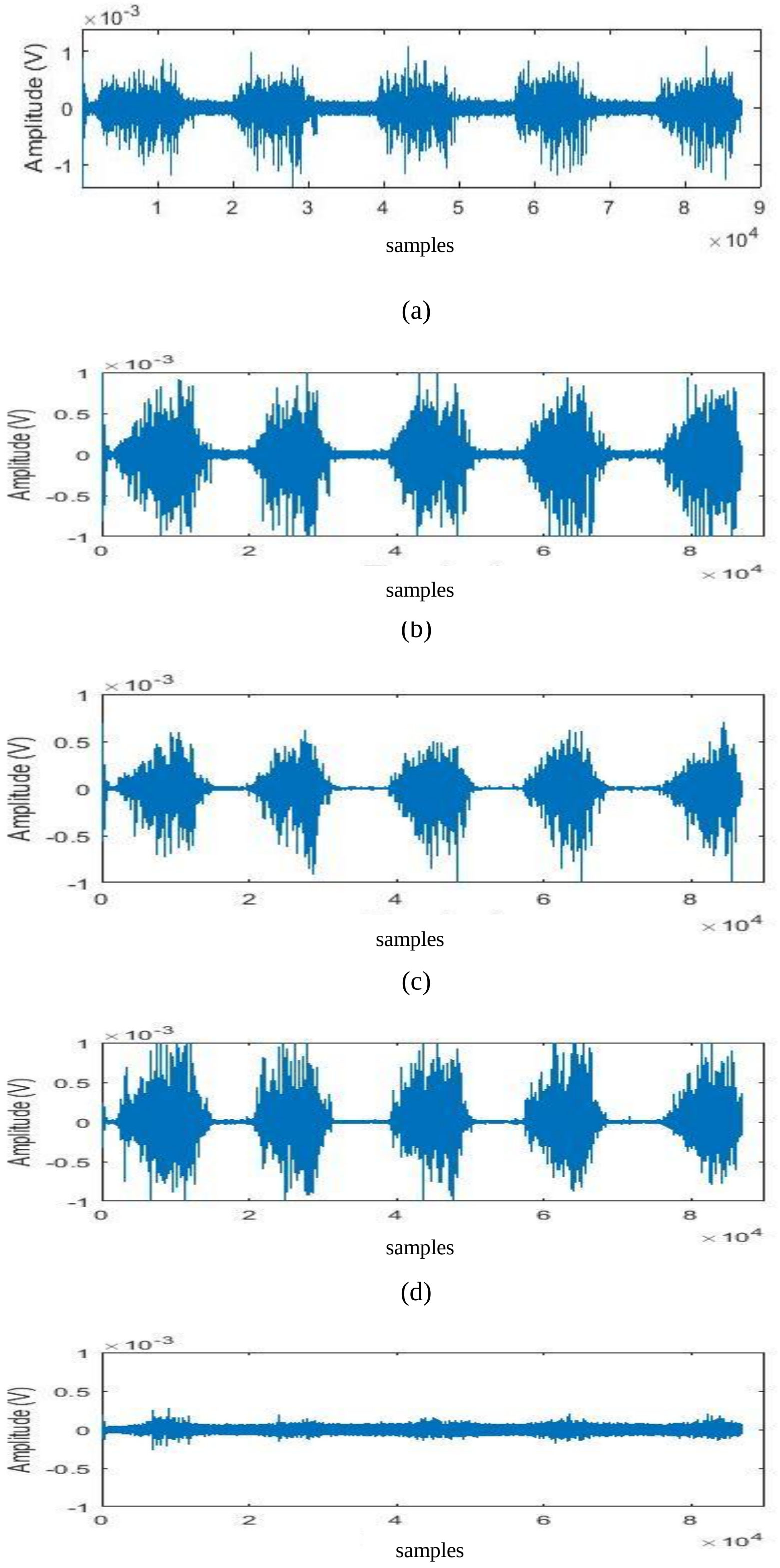
(b)

(c)

(d)

(e)

Figure 5.9 Soft gripping activity wave forms: (a) channel 1 (b) channel 2 (c) channel 3 (d) channel 4 (e) channel 5



(a)

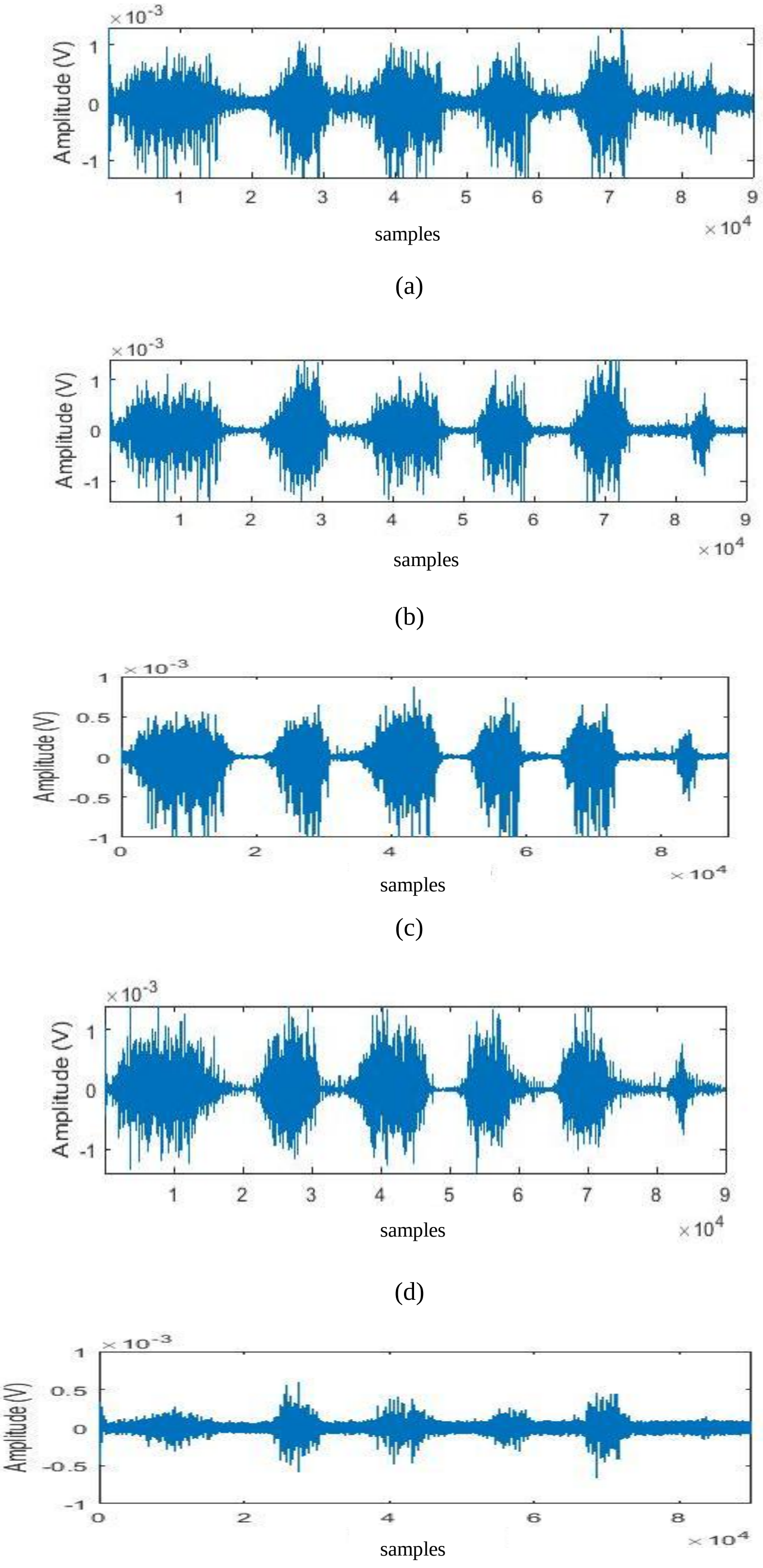
(b)

(c)

(d)

(e)

Figure 5.10 Medium gripping activity: (a) channel 1 (b) channel 2 (c) channel 3 (d) channel 4 (e) channel 5



(a)

(b)

(c)

(d)

(e)

Figure 5.11 Hard gripping activity: (a) channel 1 (b) channel 2 (c) channel 3 (d) channel 4 (e) channel 5

Table 5.1 Classification accuracies of various classifiers

S.NO.	**Classifier**	**Accuracy %**
1.	Decision Tree	43.64%
2.	Random Forest	92.61%
3.	Support Vector Machines (SVM)	81.66%
4.	Linear Discriminant Analysis (LDA)	67.14%

In classification process, the accuracy is calculated for different classifiers which are shown in Table 5.1. The accuracies of different classifiers can compare to knowing which classifier is showing better performance. In the table Random Forest classifier is showing accuracy 92.61% which is very high and decision tree classifier is showing 43.64% which is low as compare to other classifiers. For the further classification process Random Forest has been selected by this conclusion.

Table 5.2 Confusion matrix for decision tree classifier

Classes	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	423	100	44	3	103	0	55
2	124	389	25	94	33	0	95
3	32	122	432	10	72	0	10
4	30	71	73	343	16	0	2
5	97	100	44	63	255	0	36
6	130	117	85	43	193	0	86
7	50	115	80	6	140	0	255

Table 5.3 Confusion matrix for random forest classifier

Classes	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	**672**	**9**	**1**	**0**	**6**	**17**	**23**
2	**4**	**728**	**4**	**3**	**2**	**6**	**11**
3	**3**	**5**	**659**	**5**	**3**	**2**	**1**
4	**6**	**2**	**8**	**501**	**3**	**9**	**6**
5	**6**	**5**	**5**	**7**	**535**	**17**	**20**
6	**22**	**11**	**3**	**5**	**30**	**520**	**13**
7	**10**	**8**	**0**	**2**	**15**	**16**	**565**

Table 5.4 Confusion matrix for SVM classifier

Classes	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	**633**	**14**	**2**	**3**	**12**	**17**	**37**
2	**6**	**732**	**5**	**0**	**4**	**6**	**5**
3	**15**	**4**	**641**	**4**	**10**	**2**	**3**
4	**5**	**11**	**6**	**498**	**3**	**9**	**9**
5	**5**	**18**	**7**	**2**	**586**	**17**	**35**
6	**27**	**22**	**5**	**4**	**67**	**520**	**19**
7	**26**	**33**	**0**	**5**	**21**	**16**	**506**

Table 5.5 Confusion Matrix of LDA Classifier

Classes	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	**504**	**93**	**20**	**2**	**27**	**56**	**26**
2	**43**	**552**	**49**	**37**	**31**	**34**	**14**
3	**54**	**34**	**518**	**21**	**17**	**18**	**16**
4	**13**	**13**	**32**	**428**	**28**	**13**	**8**
5	**45**	**21**	**27**	**24**	**369**	**62**	**47**
6	**42**	**46**	**29**	**22**	**99**	**336**	**30**
7	**23**	**37**	**16**	**15**	**41**	**46**	**438**

A. Feature selection by random forest (mean decrease accuracy) is shown below:

The ranking of features are shown in Table 5.6 in this table the range of features vary between F1 to F50.

Table 5.6 Features and their respective channels

S.No.	Features	Respective Channel
1.	F1 to F10	Channel 1's 10 Features
2.	F11 to F20	Channel 2's 10 Features
3.	F21 to F30	Channel 3's 10 Features
4.	F31 to F40	Channel 4's 10 Features
5.	F41 to F50	Channel 5's 10 Features

Table 5.7 Ranking of Features: Feature selection by random forest (mean decrease accuracy)

1. F50	6. F29	11. F18	16. F9	21. F48	26. F20	31. F32	36. F40	41. F22	46. F41
2. F6	7. F10	12. F19	17. F15	22. F26	27.F1	32. F43	37. F11	42. F21	47. F42
3. F38	8. F36	13. F3	18. F4	23. F39	28. F28	33. F5	38. F12	43. F14	48. F27
4. F35	9. F49	14. F8	19. F46	24. F24	29. F23	34. F31	39. F45	44. F17	49. F7
5. F16	10. F34	15. F25	20. F30	25. F2	30. F13	35. F33	40. F44	45. F37	50. F47

For the classification by using random forest, feature selection is done by the Mean decrease accuracy method. In the first stage all 50 features have been taken then accuracy is calculated then top 45 features have been taken and so on shown in Table 5.7. It can be easily analyzed with the help of top 20 features the accuracy is approximately equal, with respect to all 50 feature's accuracy and when we use top 40 features the accuracy is increased relatively.

Table 5.8 Accuracies of Random Forest Classifier

Number of Features	**Accuracy in %**
50	92.66%
45	92.36%
40	93.10%
35	92.65%
30	92.33%
25	92.37%
20	91.72%
15	88.95%
10	87.31%
5	69.13%

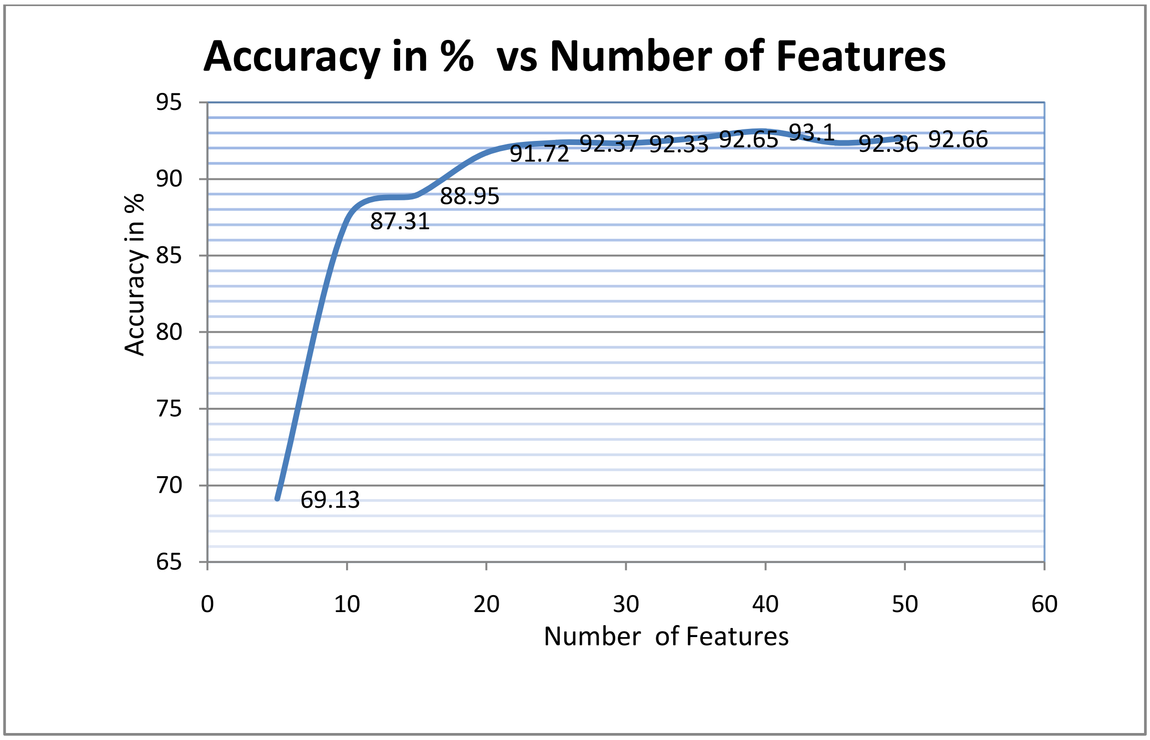


Figure 5.12 Comparative Analysis: number of features and Accuracy of Random Forest Classifier

B. Feature Reduction By channel selection is shown below

In this method, the features selection is done by selecting channel manually one by one and after those channels are selected, which gives best classification result. Further their combinations are used to increase classification performance. It can be easily analyzed that channel 2 and channel 5 do not play important role in classification, thus these channels can be ignored.

Table 5.9 Feature Reduction from each Channel

%Activity Error / **Channels**	**E_{A1}**	**E_{A2}**	**E_{A3}**	**E_{A4}**	**E_{A5}**	**E_{A6}**	**E_{A7}**	**E_{All}**
Ch1	13%	10%	12%	11%	22%	24%	17%	15.34%
Ch2	21%	18%	18%	21%	43%	41%	27%	27.11%
Ch3	14%	9%	7%	13%	22%	23%	17%	15.21%
Ch4	11%	9%	9%	14%	15%	24%	13%	13.45%
Ch5	14%	10%	10%	14%	24%	28%	17%	17.12%

Table 5.10 Feature Reduction By combination of channels

%Activity Error / **Channels**	**E_{A1}**	**E_{A2}**	**E_{A3}**	**E_{A4}**	**E_{A5}**	**E_{A6}**	**E_{A7}**	**E_{All}**
Ch1, ch4	10%	3%	6%	8%	9%	16%	8%	8.23%
Ch1, ch3	12	7%	6%	7%	16%	20%	12%	11.45%
Ch3, ch4	7%	3%	3%	7%	7%	15%	8%	7.82%
Ch1,ch3 & ch4	8%	3%	3%	7%	7%	15%	9%	7.66%

Out of these combinations channels 1,3 and 4 gives overall error of 7.66% and channels 3,4 gives overall error of 7.82%, but in first case total 30 features are being used and in second case total 20 features are being used therefore it is better to use combination of channels which uses less number of feature for classification.

5.2 Discussion

Hardware is developed for EMG data Acquisition utilizing ADS1298 IC which has 24 bit resolution and maximum 8 channels, whereas number of channels can b varied between 2 to 8. For the validation of developed EMG DAQ, data is acquired of 7 arm movement activities and classification is performed.

In the classification process, four classifiers (Decision Tree, Random Forest, Linear Discriminant Analysis, and Support Vector Machine) have been chosen for comparative study. In which the random forest classifiers shows better performance result among all classifiers. Further, feature reduction techniques were utilized, in this work two methods are adopted, first one is random forest feature reduction by mean decrease accuracy and second one is manually channel selection one by one then their combinations are used.

In the first method of feature reduction, all channels are contributed and feature of all channels are ranked and then classification is performed. The accuracy achieved by this method is 93.10% with the help of top 40 features, and with the help of top 20 features the accuracy of 92.66% is achieved.

Table 5.11 Comparison between Proposed method and other Previous work

S.No.	Author	Body Part	No. of Classes	Channels	Classifier	Accuracy
1.	He Huang et al., 2008	Shoulder	12	16	LDA	93.10%
2.	Sumit A. Raurale et al., 2009	Hand	4	6	LDA	89.20%
3.	Antonietta Stango et al., 2015	Hand	9	96	SVM	95.10%
4.	Yanjuan Geng et al, 2010	Hand	9	16	LDA	96.90%
5.	Maged S. Al-Quraishi, 2015	Ankel	4	4	KNN	96.20%
6.	Yinfeng Fang et al., 2014	Arm	10	8	KNN	99.65%
7.	M. Pla Mobarak et al., 2014	Arm	6	8	LDA	91.86%
8.	**Proposed method**	Arm	7	2	Random Forest	92.66%

In the second feature reduction technique accuracy of 92.66% is achieved with the combination of third and fourth channel only, having same number of features, however it is better to choose second method of feature reduction technique because only two channels have contributed.

The comparison of proposed and previous work is presented in Table 5.11, although little bit more accuracies achieved in previous works but the number of channels are more as compare to the proposed work.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

This study demonstrate a low cost EMG data acquisition system and its utilization . This system provides flexibility to the user for online visualization of signal during activity and also to export the data in desired format for signal processing. The power consumption is low as compare to instrumentation amplifiers based acquisition systems, as in those systems separate amplifiers IC use for each channel, where as in this system only one IC is used for 8 channels. To validate the utility of developed device arm activity recognition using EMG data is presented and further various classification techniques were compared. This work provides a potential solution for global market where cost effectiveness and portability is a key issue.

6.2 Future scope

No study is complete in itself; there is always scope for improvement. In this study the main limitations were of smaller data base and system interface with computer is wired. A database with large numbers and variety of participants would improve its value. This system have 8 channels, to make it 16 channel acquisition system a 8 channel similar circuit can be added to this with daisy chain configuration .The experiments were conducted in a quiet room, to make system more realistic the effect of noise could be taken into consideration.

This system also has wired interface so that the device has a distance limitation with respect to computer , in the future the wireless protocol can be utilized like Bluetooth , X-bee, Wifi . In this study only 5 channels out of 8 channels were utilized, for the betterment of EMG pattern classification we can utilize all 8 channels, and also reduction of the size of PCB the multilayer PCB can be used. In the near future, this system can also be used to control a robotic arm in the field of real-time processing.

LIST OF PUBLICATION

1. Sidharth Pancholi , Dr. Ravinder Agarwal“Development of low cost EMG data Acquisition system for Arm Activities Recognition”*, 2016 International Confrence on Advances in computing, Communication and Informatic(IEEE)*
2. Sidharth Pancholi , Dr. Ravinder Agarwal “Hardware Implentation of low cost EMG data Acquisition system for Arm Activities Recognition ” *Bioprocess and Biosystems Engineering - Springer, 2016 (Communicated)*

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